BALANCING AGRICULTURAL PRODUCTION, FOOD SECURITY, AND THE ENVIRONMENT IN RWANDA

An analysis of the Vital Signs Rwanda dataset

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Abstract

Global population is projected to increase to 9.8 billion people by 2050, resulting in a significant increase in food demand. Meeting this demand will necessitate agricultural intensification, which bears consequences for environmental and human health. Governments, NGOs, local decision makers, and other key stakeholders seeking to manage agricultural development safely and sustainably need quantitative analytical information on the efficacy of various agricultural yield intensification strategies, and the associated co-benefits and tradeoffs for human and ecological health. Conservation International seeks to address this need through Vital Signs, a data collection and monitoring program which has been implemented in sub-Saharan Africa. Through analysis of Vital Signs data collected in Rwanda, this project explores the relationships between yield and agricultural practices, and the association between farmer practice and household food security. For most crops, we did not find a strong positive association between the use of fertilizer and/or pesticides and yield (kg/hectare) reported by farmers. This finding suggests that agricultural development programs may be most productive when aimed at training smallholder farmers (the demographic most represented in Vital Signs data) on the correct usage and timing of these inputs, which theoretically can increase yield intensity. Further, our analysis generally found the use of intercropping as a strategy did not have significant negative associations with yield of a given primary crop (with the exception of maize), indicating that adding a compatible secondary crop to a plot may provide an extra benefit. In examining household food security, we find that households which are more food secure are more likely to employ intercropping as a strategy, and also use greater quantities of fertilizer and pesticides. Finally, this project examined the limitations of the Vital Signs database, and provides specific recommendations for improvement of data collection protocols.

Executive Summary

Rwanda is a small, densely populated nation in East Africa where the vast majority of the population relies on subsistence agriculture. Most land is already devoted to farming, save for a few ecologically valuable protected areas, though pressure for agricultural extensification is mounting. Broadly, agricultural expansion carries environmental consequences as natural lands are converted for new uses and thus biodiversity and ecosystem services such as soil retention and water quality are threatened.

Policy makers, regional extension agents, and farmers all seek to make agricultural management decisions that maximize agricultural production. Often, decision makers intend to, at the same time, improve human well-being and minimize ecological harm. There remains, however, a lack of information to guide efforts to this end, especially concerning smallholder farms. Conservation International developed the Vital Signs data collection protocols in an attempt to fill this knowledge gap, particularly at the small scale. Analyzing the efficacy of farmer practice, and tradeoffs and synergies between agricultural productivity and ecological and human wellbeing can provide important insights for the best path towards sustainable intensification.

Vital Signs is an open-source database with indicators intended to be useful for examining these synergies and tradeoffs in sub-Saharan Africa. The data sets 1000+ indicators are gathered from biophysical data collection and systematic deployment of household surveys. Vital Signs has successfully launched in four countries- Rwanda, Ghana, Tanzania, and Uganda, although as of March 2019, Rwanda is the only country to have fully completed two rounds of data collection.

Now in its initial post collection phase, Vital Signs data had prior to this analysis yet to be thoroughly analyzed. Evaluating only Vital Signs data from Rwanda, we explored the relationships between agricultural practice (defined to include the application or use of pesticides, fertilizers, improved/purchased seeds, erosion control strategies, and intercropping), yield (defined as kgs of crop harvest per hectare of cultivated area), food security, and the environment in Rwanda. Our project also provides an exploration of the data sets limitations, and provides recommendations to improve protocols and inform future Vital Signs efforts.

To this end, we define four research questions. From Vital Signs data:

1. What are the discernable relationships between various agricultural practices and yield?
2. How do the agricultural practices of farmers yielding higher (top quartile of harvest quantity) compare to the practices of farmers with lower yield (lower three quartiles)?
3. What is the relationship between agricultural practice and household food security?
4. What are the limitations of the Vital Signs data and how can data collection protocols be improved to make the data set more robust?

To answer these questions, we disaggregated the data by crop variety, and ran a systematic series of mean comparison tests and separate sets of single and multiple regression models. Food security was analyzed by utilizing a household food security index score, developed to closely parallel the USAID index: "Household Food Insecurity Access Scale" (HFIAS).

Broadly, our results do not indicate strong positive relationships between analyzed agricultural practices and reported yield. This suggests that, if farmers are reporting correctly, then the application of fertilizers and pesticides on rural household plots in Rwanda and the use of improved purchased seeds and erosion control techniques, is not translating to significantly higher yields for most crops. If intensification is the agricultural management objective, programs should therefore focus on training for the correct usage and timing of the application of these inputs. While this remains an overarching takeaway of this analysis, results varied by crop type, and any eventual agricultural management recommendations should be crop specific. In some tests, for example, inorganic fertilizer use was associated with higher yield (Irish potatoes, maize, and wheat), although the relative magnitude of the positive association was often found to be small.

Further, in a simple comparison of the mean quantity of pesticides and fertilizers applied between top performing farmers and bottom performing farmers, the top performers applied more of these inputs.

Households that intercropped were found to be significantly more food secure, and intercropping was not usually associated with significantly lower yield of the identified 'main crop' on a given field. It is important to note that while this is a general pattern we observed, this was not the case for every crop in every test. In particular, intercropping was associated with lower yield of maize as a main crop. For other crops, our findings suggest a certain benefit to intercropping, as any harvest of secondary crops is an added value of the space, compared to utilization of the same space in monoculture.

Our analysis also found a number of limitations within the Vital Signs data set, and we make several recommendations to the Vital Signs data collection protocols to improve the robustness of future data. Currently, Vital Signs is considerably broad in the types of indicators that it covers, but shallow in its sample size. Sample size proved to be the most limiting aspect of analysis. Expanding sample size can be very resource intensive. Therefore, we recommend that sample size be expanded strategically based on the categories of research questions that are most relevant to the use case, such as those surrounding agricultural practice and food security. Having pre-defined research questions can aid processes of limiting the scope of indicators.

A second issue was that selection of survey questions did not always match the desired analyses. For example, the food security index was limited to examining only one aspect of food security because questions were not present to cover all aspects of food security, and many questions were present that were not relevant to the main research questions. We recommend the removal of the least relevant survey questions, and the addition of questions that may bolster the desired analyses. We also ran into data quality issues such as outliers and data missingness. This can be addressed through the addition of a number of verification criteria to data collection protocols.

Lastly, we suggest that producing a complete panel data set will improve the Vital Signs data's ability to inform agricultural management decisions in a meaningful way. This can be resource intensive, but a shortened questionnaire coupled repeated surveying overtime may prove beneficial, and improve Vital Signs ability to answer key questions.

A further specific recommendation is to add a household survey question which asks farmers how long a given practice has been employed. As benefits of applying fertilizers are actualized over time as soil quality slowly improves, adding a time-bound element would improve inference ability in analyses. The same is true for other agricultural practices included in the database.

Vital Signs is a unique data set in its scale and integration across disciplines, although further data collection and analyses are needed to ensure that it can answer important questions about sustainable agriculture. Our project highlights some interesting findings from one of the first major explorations of Vital Signs data, and offers suggestions on ways that protocols can be improved to aid future research.

Objectives

This analysis aims to analyze the relationships between agricultural practices, yield, food security, and the environment in Rwanda, and explore how these relationships can inform key stakeholders as they make agricultural development decisions into the future. As one of the first in-depth analyses of the Vital Signs Rwanda dataset, this research also intends to explore the limitations of the database, and make suggestions for the improvement of data management and data collection protocols.

Research Questions

1. What are the discernable relationships between various agricultural practices and yield?
2. How do the agricultural practices of farmers yielding higher (top quartile of harvest quantity per area) compare to the practices of farmers with lower yield (lower three quartiles)?
3. What is the relationship between agricultural practice and household food security?
4. What are the limitations of the Vital Signs dataset and how can data collection protocols be improved to make the dataset more robust?

Significance

The global population is expected to grow from 7.7 billion people today, to approximately 9.8 billion by the year 2050 (UN 2017). With this rising population comes a rising demand for food. The United Nations Food and Agriculture Organization (FAO) projects that global agricultural production must increase 50% by 2050 in order to meet this demand (FAO 2017). Other projections indicate that agricultural demand will need to increase by at least twice that amount (100% to 110%), as household income and consumption of resource-intensive foods like meat increase (Tilman 2011). This increase in agricultural demand will strain an agricultural system that has already expanded considerably and will increase pressure on ecosystems. This can lead to severe environmental degradation, habitat fragmentation, and harm to biodiversity, water quality, and other ecosystem services we rely on.

Because more than half of the population growth by 2050 is projected to occur in Africa, many African nations are actively pursuing agricultural development plans to meet these rising food demands in a sustainable way that minimizes harm to their valuable ecosystems (UN 2017; MINECOFIN 2000). However, these agricultural development decisions require large amounts of information at relevant geographic and temporal scales that often do not exist.

Data for the Vital Signs program has been collected across Ghana, Rwanda, Tanzania, and Uganda; Rwanda has the most complete collection of data and has yet to be thoroughly analyzed. Focused only on Rwanda, the purpose of our project is to analyze the Vital Signs data set to examine current relationships between agricultural practices and production, food security, and environmental consequences. In addition, we seek to identify any limitations in the Vital Signs data to inform future data collection efforts.

Background

Rwanda is a country that exemplifies the conflicting pressures of agricultural expansion to address food security with the need to preserve sensitive habitat and valuable ecosystem services. Already the second most densely populated nation in Africa, Rwanda has a population growth rate of 2.6% annually, a rate which is only expected to increase as the large younger generation comes into reproductive potential (NISR 2014, MINAGRI 2015). Agriculture has already expanded rapidly to meet increased food demand; 33% of Rwanda's national GDP is based in agriculture as of 2015, with the vast majority of that agriculture consisting of smallholder farmers (MINAGRI 2015). Agriculture also accounts for 72% of employment countrywide (FAO 2018). Yet despite the fact that the majority of Rwandans are farmers and the majority of land in Rwanda is used for farmland and pasture, Rwanda struggles to feed their growing population.

Food Security

Nutrition and food security is a global, primary development goal established by the 1996 World Food Summit. The summit defined food security as "when all people, at all times, have physical and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life" (World Food Summit 1996). The goal was later adopted in 2000 by the United Nations in their UN Millennium Declaration, which sought to halve global hunger by 2015 (United Nations 2000).

Food security is assessed on four pillars according to the Food and Agriculture Organization of the United Nations (FAO): availability, access, utilization, and stability. Availability deals with food production, access deals with household food security, utilization deals with individual nutrition, and stability deals with how the three previous pillars change over time (FAO 2008). One common index to quantify food security is the Household Food Insecurity Access Scale (HFIAS). The HFIAS focuses on the access pillar of food security. The index score ranges from 0 to 27, with 27 being most food insecure. This index was developed by USAID's Food and Nutrition Technical Assistance (FANTA) project (Coates et al. 2007). Rwanda has major issues with poverty and food security; 39.1% of Rwanda's population is below the poverty line as of 2014 (NISR 2014) and 35% of children under 5 are considered chronically malnourished according to the World Food Programme (WFP 2018). According to the EIU, in 2018, Rwanda's Food Security Index score stands at 38.4, where a score of 100 is most food secure. Rwanda was ranked 93rd globally in terms of food security according to the Global Food Security Index (EIU 2018). If the Rwandan government aims to feed more people without importing more food, agricultural yields across the country will need to increase significantly to meet that demand.

Intensification over Extensification

At the broadest level, crop yield can increase in one of two ways - extensification or intensification. Extensification refers to increasing agricultural yield by clearing more land to farm on, while intensification refers to increasing yield by producing more crops in existing fields. Globally, nearly 40% of ice-free land is already dedicated to agriculture and livestock grazing; within Rwanda that percentage increases to 73% (Ramankutty et al 2008). Extensification leads to habitat fragmentation and loss and is one of the leading causes of extinction. Rwanda is an important area for species conservation due to the high levels of species richness, endemism, and threatened status. Most of the biodiversity in Rwanda is located along the Albertine Rift, which spans through eastern Democratic Republic of Congo, Southwestern Uganda and Northern Rwanda (Plumptre et al. 2007). Nonetheless, there is a risk that this biodiversity will be overlooked when large international NGOs are targeting conservation hotspots, because though it is thought that exceptional concentrations of endemic species are undergoing considerable loss of habitat in the Albertine Rift, there is still not sufficient data or documentation to officially list this region a conservation hotspot. It remains, however, a recognized important site for biodiversity (Myers et al. 2000).

All three national parks in Rwanda – Akagera, Nyungwe, and Volcanoes – are protected areas that provide exceptional ecosystem services such as biodiversity, water quality, air quality, and ecotourism. It is estimated that 70% of water obtained in Rwanda comes from National Parks (Plumptre et al 2007). Comparatively, Nyungwe Park has the highest levels of both endemic and globally threatened species. Volcanoes Park is best known for hosting one of only two remaining populations of endangered mountain gorillas (*Gorilla beringei beringei*). Mountain gorillas are also a keystone species critical to providing balance in their ecosystem, and they provide an economic service in the form of ecotourism; tourists pay over $1,000 USD to spend just an hour observing them in the wild. Akagera Park is the largest protected wetland in Central Africa and the only remaining refuge for savannah adapted species in Rwanda. A notable case study in wildlife restoration, many species that were extirpated during the Rwandan Civil War, such as lions, were successfully re-established within the park over the last decade. Only the national parks, a few small protected areas, and highly mountainous non-arable regions remain unfarmed and undeveloped within Rwanda. However, as agricultural pressures mount, the risk of encroachment into these ecologically important areas will likely increase. Therefore, other solutions must be found that minimize expansion of farming by intensifying crop production on land already being farmed. Methods of intensification examined in this paper include intercropping, erosion control, and use of pesticides and fertilizer (Deininger et. al 2018; Brooker et al. 2015; Snapp et al. 2010).

Improving Agricultural Yield

Decision makers in Rwanda must balance the need to address poverty and food insecurity through agricultural production with protecting unique and valuable ecosystems and wildlife. Increasing agricultural yield sustainably requires analysis of the efficacy of various agricultural practices in improving yield and food security, and their potential environmental consequences. Competition for arable land is high in this small and hilly nation of approximately 2.6 million hectares, and farmers must make the best possible use of limited space. According to the Rwandan government's 2018 Seasonal Agricultural Survey, the average farmer owns a plot of only 0.12 hectares on which to grow their crops. Many spaces that can be farmed include sub-optimal, steep hillsides and low marshlands.

Eliminating agricultural yield gaps is critical to addressing food insecurity in low yield nations like Rwanda (Tilman 2011). A yield gap is defined as the difference between the average or actual yield of farmers and the maximum yield that is achievable under best agricultural practices. This maximum yield, also known as potential yield, occurs when nutrients and/or water are not limiting variables (van Ittersum and Cassman 2013). These yield gaps are usually attributed to a lack of modern inputs and technologies as well as biophysical limitations such as poor soil fertility, nutrient availability, and water access (Tilman 2011; Tittonell and Giller 2013). Smallholder farm yield gaps are pervasive in many African nations and recent genetic improvements that offer yield gains have not provided many improvements for smallholder farmers. This is because the greatest biophysical yield limitation in Africa is (broadly) poor soil fertility. Soil resistance to fertilizer inputs and increased labor required in degraded soil contributes to low yield and therefore chronic poverty (Tittonell & Giller 2013). Research indicates that improving soil fertility is also one of the most critical factors for developing climate change resilience and environmental sustainability in Rwandan agriculture. Other areas for yield improvement include: data management and tools, mechanization, water management, seed quality, and vegetable and livestock integration (Deininger et. al 2018).

Intercropping may be an effective method to intensify agricultural output in some cases. Intercropping is defined as the practice of growing multiple crop species together in the same field at the same time. Some studies have found a significant positive correlation between intercropping and yield and yield stability attributed in part to increased soil carbon and nitrogen (Brooker et al. 2015, Snapp et al. 2010). While intercropping is often lauded as an efficient means of growing more with less land, the literature is mixed on whether this is *always* the case. While intercropping may increase yield, the results can be crop or site-specific (Himmelstein et al. 2017; Dallimer et al. 2018; Swanepoel et al. 2018). Other literature indicates that while intercropping may not increase yield in certain areas, it reduces variance in yield from year to year, which farmers may favor for more consistent profits or food security (Saeur et al. 2018; Zhu, in prep). In terms of environmental benefits, intercropping may improve soil quality by reducing erosion, and may improve water quality by increasing nutrient uptake and thus reducing the flow of nutrients into waterways (Kremen and Miles 2012; Wood et al. 2015; Dwivedi et al. 2015). Another sustainable intensification practice that may be important to agricultural development is erosion control; erosion control leads to greater retention of water and fertile topsoil. This is critical in a hilly country like Rwanda, where the majority of agricultural land is on hillsides and intense rainy seasons frequently lead to severe erosion including landslides. Additionally, there is very little irrigation so water retention is a big added benefit. Government surveys indicate that 67% of smallholder farmers currently engage in erosion control activities (MINAGRI, 2018).

Inputs such as fertilizer and pesticides can be critical to maximizing agricultural yield, particularly in places like Rwanda that typically rely on low-input agriculture, and broadly in areas with poor soil quality (Ciceri & Allanore 2019; Abate et al. 2000). However, these inputs can only maximize yield to a point and overuse can be harmful to water quality and biodiversity (Clay et al. 1995). Inorganic fertilizers and pesticides also require an up-front cost that may be prohibitive for the poorest farmers if these inputs are not properly and effectively subsidized (Nahayo et al. 2017).

It is critical that decision makers consider the trade-offs of these various intensification methods in order to maximize crop yield while minimizing ecological harm and human health risk. At the same time, it's also important to consider the existing policy framework and institutions that may influence the implementation of their agricultural development recommendations.

Policy Landscape

The Rwandan government recognizes the critical role of the agricultural sector in addressing poverty and food insecurity and has made it a major pillar of their national development strategy. In 2000, as Rwanda recovered from the war and genocide of the 1990's, the new Rwandan government produced a series of development goals for the nation leading up to the year 2020. This document, Vision 2020, provided a framework of government priorities, and has been recently updated to Vision 2050. One pillar of these priorities was the overhaul of Rwanda's agricultural sector. The stated goal was to grow the economy, reduce poverty, and increase food security. To accomplish this, the government wishes to increase agricultural productivity as much as possible (MINECOFIN 2000). The responsibilities of this goal have primarily fallen to the Rwandan Government's Ministry of Agriculture and Animal Resources (MINAGRI), who oversee agricultural development and food security (MINAGRI 2015).

MINAGRI has developed the National Agricultural Policy to outline how they will achieve the goals of the agricultural pillar of Vision 2020. This policy focuses on increasing productivity and intensifying agriculture sustainably to minimize environmental impacts. To increase productivity, the policy plan emphasizes the use of modern inputs such as fertilizers, pesticides, and improved seed varietals. Farmers are also encouraged to switch to high-value crops and to consolidate farm plots through farmer cooperatives. To sustainably increase agricultural production, the policy emphasizes intensification to increase yield without expanding agricultural area. The policy also focuses on addressing erosion problems to protect both soil and water quality and considering the potential environmental impacts of mechanization and modern inputs (MINAGRI 2017).

MINAGRI oversees several programs meant to address the goals of the National Agricultural Policy, but the Crop Intensification Program (CIP) is that which is most relevant to this project. Initiated in 2007, the CIP mission is to increase national agricultural productivity through intensification practices and modernization. Intensification is defined as increasing agricultural productivity on a given plot of land, as opposed to expanding land area used for production (extensification). CIP intensification practices include consolidating smallholder farms, moving from traditional intercropping to monocropping, and increasing farmer access to extension services. Extension services include education on best practices, food storage facilities, and access to modern inputs at a subsidized price. These services are provided by regional extension agents. Inputs include improved seeds, fertilizer, pesticides, irrigation, and mechanization. Fertilizers are distributed in partnership with local, private distributors. CIP dictates which crops are grown, and when and where they are planted. The program focuses on six main crops: maize, beans, rice, wheat, Irish potatoes, and cassava (MINAGRI 2011).

Numerous academic analyses of the CIP indicate overall agricultural yield may be increasing, but there are serious limitations that may reduce the resilience of farmers to risk. First, farmer input in program design was limited, and this top-down approach may not capture all of the on-the-ground realities of program implementation. Also, monocropping can increase farmer risk if a crop fails, and leaves farmers vulnerable to fluctuations of that single crops price if they choose to sell excess crops. The poorest farmers may not be able to afford the required inputs to intensify properly, even with government subsidies. There is also evidence that consolidation programs do not increase productivity (Blarel et al. 1992). All of these factors increase the risk to farmers, and particularly poor farmers. This can serve to increase household food insecurity and reduces economic well-being, even if overall yield appears to be improving (Clay 2017, Nahayo et al. 2017, Cioffo et al. 2016).

An additional MINAGRI program with relevance to this project is the One Cow per Poor Family Program, or Girinka Program. This program is primarily intended to address poverty and food insecurity by providing a dairy cow to the lowest-income households in Rwanda. The intent is to provide a source of dairy, meat, and added income if those products can then be sold. It is of significance that these cows also act as a source of organic fertilizer (manure) (MINAGRI 2018).

Assessments of the Girinka Program have indicated that it has been at least somewhat effective, although with limitations particularly for the poorest households. Approximately one third of households have been reached by the program, and participation is positively associated with household food security and per hectare crop production (Nilsson et al. 2019; Paul et al. 2018). There has been insufficient fodder for the poorest households in the program, and a lack of training on livestock upkeep (Klapwijk et al. 2014). Manure use from the program as organic fertilizer is also limited by a lack of tools for moving manure, and lack of proximity to fields. There is also a lack of training on best practices for manure application (Kim et al. 2013).

It is within this policy landscape that decision makers must push for effective agricultural development. If we can discern relationships between agricultural practices, crop yield, and food security at a local scale, policy makers will be able to make more informed agricultural development decisions that balance agricultural production, human well-being, and environmental health. This is particularly critical in countries like Rwanda, where these needs are often in conflict and the policy landscape does not always reflect the most efficacious practices.

Data

Vital Signs is an open-source database that examines indicators of agricultural practices, ecosystem health, and human wellbeing in sub-Saharan African nations. Data is collected on a hierarchy of scales referred to in the data protocols as 'landscapes' (the highest level), 'E-plots' (within each landscape, defined below), and finally at the individual household and field levels (Figure 1.1). In Rwanda, two rounds of data collection have taken place, spaced approximately one year apart. In total, data was collected from 10 landscapes, which consist of 10 km by 10 km parcels (6 were sampled in the first round and all 10 in the second). Landscapes were purposefully placed in the distinct agro-ecological zones of Rwanda. Within each landscape are 10 randomly placed 20 m x 20 m 'E-plots', named for the shape of where biophysical data is collected at even point intervals within these boxes (Figure 1.2). Biophysical data includes vegetation, water quality, soil quality and chemical content, and tree species and size. For every E-plot, 3 households are interviewed which are in close proximity to 3 corners of the E-plot (Figure 1.2). Household interviews include questions on demographics, labor market participation, food security, nutrition, water sources, other sources of income, as well as, significant for our analysis, agricultural information including the number and size of plots cultivated by a member of the household, fertilizer use, pesticide use, irrigation and erosion control methods, yield, and the market value of harvested crops. There were 280 unique households within Vital Signs Rwanda data, with 154 households sampled in round 1, and 272 households sampled in round 2.

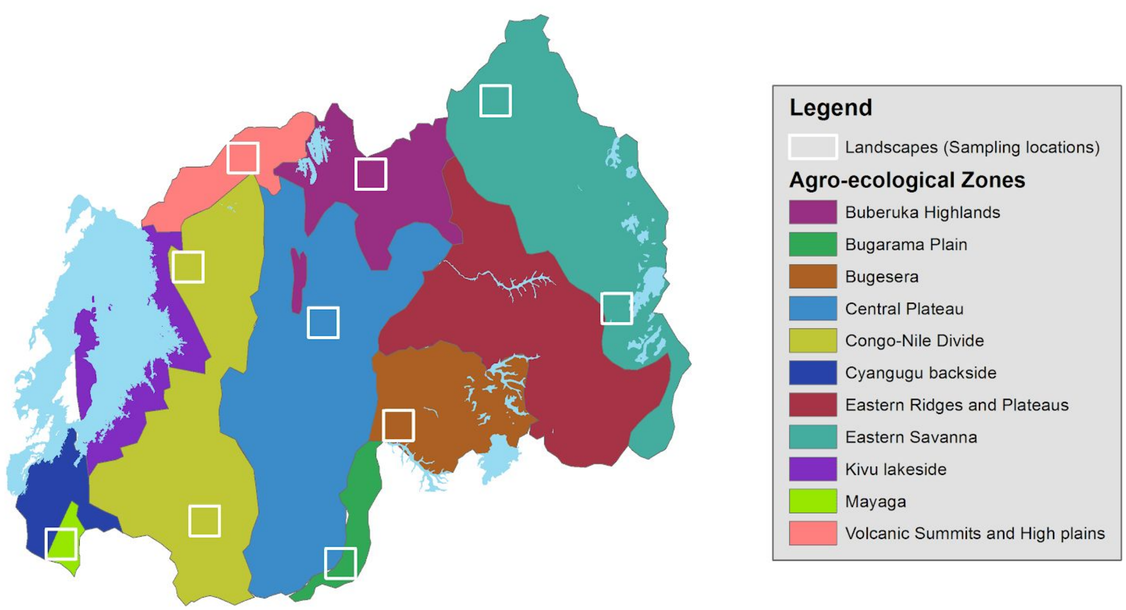

Figure 1.1 Landscapes and agro-ecological zones from Vital Signs data collection in Rwanda.

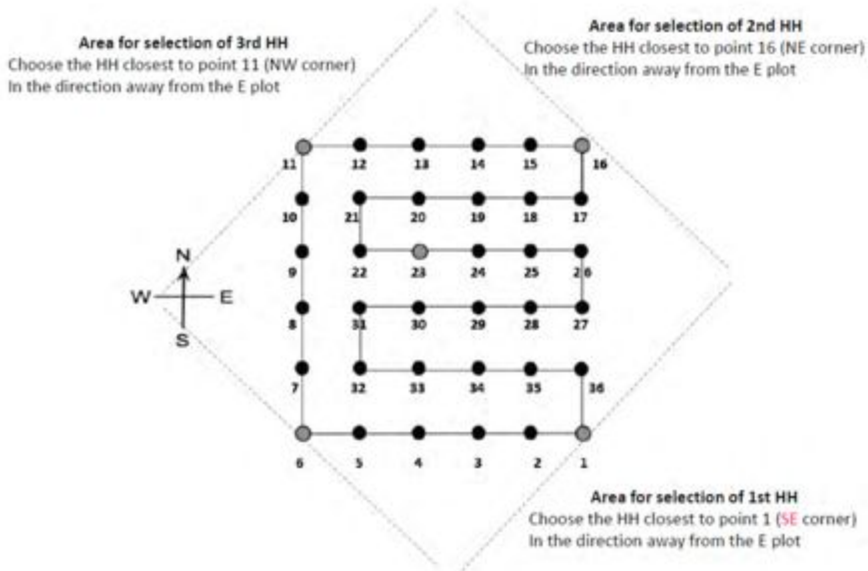

Figure 1.2 Household selection near E-plots. Efforts are made to choose households on opposing corners of the E-plot (Vital Signs Household Survey Protocol 2.0).

Methods

Data Wrangling and Manipulation

With the exception of initial data exploration and characterization of descriptive statistics, only Vital Signs data observations from Rwanda were analyzed by this project. For the purposes of equal comparison, farmer input and output data were filtered to only retain observations from plots which the farmer reported as: 'under cultivation'. All tests were crop specific, that is, performed separately for each crop varietal.

Due to sample size limitations, our analysis of the effects of pesticides, fertilizers and erosion control techniques did not explore each type of these independently, but rather as a summed total. For example, analyses only looked at the total quantity of pesticides applied, broadly defined to also include herbicides and fungicides, though did not perform specific analyses on each *variety* of pesticide used. The same was true for fertilizers, although the total sum of organic and inorganic fertilizers were analyzed separately. With greater sample size, analyses could be improved by separately considering each variety of fertilizer and pesticide used, and each type of erosion control strategy applied, and this information is available from the Vital Signs indicators.

Pesticides were listed in both liters and kilograms in the data (57% of farmers reported in kilograms), but for the purposes of this analysis, a liter of pesticide was considered to be equivalent to a kilogram of pesticide, as liquid pesticides were assumed to be water based, and therefore roughly equivalent to the density of water.

For many crops, yield outliers appeared that were so far away from the distribution of all other observations, it was assumed there was some data misentry. To reduce the influence of these outliers, data for each crop were trimmed of the highest and lowest 2.5% of yield observations.

Finally, on intercropped fields, data were filtered such that only the yields of the crop variety that the farmer reported as each plot's "main-crop" were compared. Here, we reasoned that the efficacy of agricultural strategies should be compared across as similar of fields as possible.

I. Yield and Agricultural Practice

The relationship between yield and agricultural practice was analyzed via a systematic series of Welch's t-tests, clustered linear models, and clustered multiple regression models. These tests were run in succession of each other for each crop of adequate sample size. Constructing the analysis in this manner provides an opportunity to look at broader trends and patterns from results of statistical tests of varying complexity. Where t-test results simply demonstrate whether all farmers in the database who applied a given practice when cultivating a given crop received significantly higher yields than those that didn't apply that practice, regression models layer on complexity and allowed us to control for variables which may contribute to observed differences, such as differing biophysical characteristics of plot location (Vital Signs 'Landscape') and growing season. Finally, looking at each farmer practice in a regression model by itself (as the only explanatory variable), and in a separate multiple regression model which included all practices for each crop, provides the opportunity to look at simultaneous and isolated associations with each practice and reported crop yield.

Because there were multiple periods of reporting for some of the same plots (two rounds of data collection, plus multiple growing seasons reported in each) each regression model clustered robust standard errors on a unique plot identification number. Clustering in this manner adjust standard error estimates to account for the fact that the yield of a given crop is partially dependent on plot-specific characteristics. Soil conditions such as nutrient availability are highly localized, and are impacted by the selection of crops grown in the same area during previous seasons, and the practices applied to each plot over time. Further, clustering on unique plot id accounts for differing sunlight availability, which is also plot specific.

In each case, tests were run on each crop in the database with adequate sample size. For t-tests, adequate sample size was determined to be a minimum of 15 data points from plots which grew that crop and applied a given practice, and a minimum of an additional 15 which grew the same crop but didn't apply a given practice. For clustered linear models, adequate sample size was determined to be a minimum of 30 total observations of that crop, with at least 5 having applied a given practice. Multiple regression models were only run on eight crops with the greatest total sample size.

Yield was defined as kilograms of harvested crop per hectare of area cultivated with that crop. These metrics were self reported by farmers as part of the Vital Signs household survey protocols, with only unit normalization required. A caveat here is that if a given plot was not entirely planted with its "main-crop", farmers were asked to estimate the total coverage of this crop with possible responses being: ¼, ½ , ¾, or almost all. These were assumed to be perfectly representative of the true area, with 'almost all' approximated as equal to the full area of the field.

a) Mean Yield Comparison

Welch's two-sample one-sided t-tests were used to compare the mean yield of all observations of a given crop which received a given practice (quantity irrelevant), to all observations of the same crop that did not receive that practice. This provided a coarse examination of the correlation between a given agricultural practice and yield, but does not account for any other agricultural practices employed, or other variables which may explain observed differences. For all practices except intercropping, the alternative hypothesis was that crops originating from plots which applied a given practice produced a higher yield than plots that did not. This is based on the assumption that agricultural practices are applied to increase yield, and thus results provide a first glimpse at whether or not a given practice is 'working'.

For intercropping, a Welch's two-sample *two sided* t-test was used. Here, the alternative hypothesis was that plots which intercropped produced a difference in yield from those grown in a monoculture. This test was used because yield was reported in a crop specific manner of a fields 'main crop'. Therefore, if two fields, one which is employing intercropping, and the other which is growing its main crop in a monoculture, do not produce a difference in yield of a given 'main crop', then the secondary harvest from the field which intercropped has provided the benefit of an extra crops harvest. Thus, there can be a benefit to intercropping even if employing the strategy does not boost the yield of a given 'main crop', and a two-sided t-test is one way to evaluate whether such a benefit exists.

b) Clustered Linear Models

Linear regression models were run for each crop with adequate sample size, with yield regressed on each agricultural practice as the only explanatory variable. Each model included landscape, round, and season as control variables. Vital Signs landscape was used as a control as the distinct biophysical characteristics of each agro-ecological region, which determined the non-random placement of landscapes, is assumed to have an effect on the efficacy of each agricultural practice, and on yield broadly. Round was used as a control as any differences in weather patterns, etc. between the two years of data collection may have also impacted yield and practice efficacy, as likely does growing season (short-rainy, or long-rainy).

The following general form was used to develop the regression equation, with standard errors clustered on unique plot id:

Yield for a given crop (kg per hectare) ~ Practice + Landscape + Round + Season

c) Clustered Multiple Linear Regression Models

Multiple linear regressions utilized the same equation as above, except a single model was run for each crop which simultaneously evaluated each farmer practice. This analysis was applied to eight crops in the database of greatest sample size (each had over 30 observations). Including more than these eight would have meant regressing on crops which had low sample size, and a low representation of observations having received certain practices. Each model again clustered robust standard errors on unique plot id, with the same control variables used as in other models (landscape, round and season).

The following general form was used to develop the regression equation, with standard errors clustered on unique plot id:

Yield for a given crop (kg per hectare) ~ Intercropping + Pesticides + Organic Fertilizer + Inorganic Fertilizer + Improved Seeds + Erosion Controls + Landscape + Round + Season

d) Crop Value across Landscape

Finally, we examined which crops translated to the highest valued harvests in each landscape (farmer reported total harvested crop value per hectare of area cultivated). The findings from this section of the analysis provide useful information for evaluating potential future changes if farmers are to gradually switch from growing lower value crops to higher value crops, as economic theory may predict. The results of this analysis may allow for predictions on what crop types and practices may become more common over time.

We compiled the mean value (reported RWF/hectare) for each crop grown in each landscape. We then removed any crop types for a given landscape that had a sample size of less than 5. We chose to eliminate these crops with a low sample size for two reasons. Firstly, because we think it is less likely that farmers would switch to growing a crop if there are already so few people growing that crop- as this may indicate this is a specific niche crop, and may not have broader value to be captured. Secondly, we can't be as confident in the farmer's estimate of value if we have too few entries to average. However, because overall sample size was already limited, we wanted to avoid over-restricting sample size. For that reason, we chose 5 to balance these two concerns. We then compiled tables showing the top three highest valued crops in each landscape.

II. Yield Gap Analysis

The next step in our analysis was to explore yield gap by crop type. The purpose of the yield gap analysis was to compare the practices of the best performing farmers to the rest of farmers for each crop type. The analysis was once again disaggregated by crop type. Note that this analysis was not disaggregated by landscape due to insufficient sample size, and may therefore be affected by landscape or other confounding variables.

First, after data trimming, high-performing farmers were separated from under-performing farmers for each crop. Top farmers were defined as receiving yields in the top quartile (kg per hectare), while underperforming farmers were defined as falling in the bottom three quartiles. This division at the quartile level was based on other studies of yield gaps found in literature review (Fermont 2009, Ciampitti 2014). The second step was to identify how the amount of agricultural inputs of the top quartile differ from those of the underperforming farmers. Agricultural inputs included inorganic fertilizer, organic fertilizer, and pesticides.

Welch's two-sample one-sided t-tests were used to test whether mean quantities of pesticides, organic fertilizer, and inorganic fertilizer used on fields were higher in the top quartile than mean quantities of inputs used in the lower quartiles. This analysis was conducted in order to provide correlative evidence for how use of inputs differed between the high and low performing groups and to try and elucidate general patterns across various crop types.

III. Food Security Analysis

Previous work by Conservation International (unpublished Vital Signs data repository) used Vital Signs household survey results to score household food insecurity utilizing methodology which aimed to parallel the USAID "Household Food Insecurity Access Scale" (Coates et al. 2007) index score, or HFIAS. This methodology was chosen as the official HFIAS questionnaire sufficiently overlaps with questions included in Vital Signs household surveys, such that calculating a similar score is possible.

Questions from the Vital Signs Household Survey asked the member of each surveyed household whom was 'most responsible for preparing family meals' a series of questions about their household's access to food within the last 7 days (table 1.1). For each question, responses had a possible range of 0-7 (days in the past week in which the specified event was experienced by someone in the home). With 8 scored questions, the total maximum score was 56, with higher numbers corresponding to more food *insecure* households, all else equal.

Table 1.1. Vital Signs household survey questions included in scoring food security index. Questions were part of the larger household survey, and were asked of the household member most responsible for food preparation.

How many times in the last week (number of days) did you or someone in your family:
1. Rely on less preferred foods?
2. Limit the variety of foods eaten?
3. Limit portion size at meal-times?
4. Reduce the number of meals eaten in a day?
5. Restrict consumption by adults for small children to eat?
6. Borrow food, or rely on help from a friend or relative?
7. Had no food of any kind in the household?
8. Go a whole day and night without eating?

As some households were surveyed in both rounds, an average household score was derived for each household. We then compared the agricultural practices employed by more food secure households, to those employed by less food secure households.

Simple linear regression models regressed food insecurity score on household agricultural practices. Households were placed in binary categories for each farmer practice. For example, households which intercropped any field in any round, were placed into a "sometimes intercrop" group, whereas households which never intercropped were placed into a "never intercrop" group. These were then used as levels of an intercropping factor in a linear regression model. The same methods were repeated for the application of fertilizer and pesticides, with separate models run for each. Each regression included a control variables for Vital Signs landscape, as food security varies regionally across Rwanda.

Next, we analyzed whether there were any discernible patterns in the different types of crops that households with varying food insecurity scores were growing. Based on index results, we took four groups of food security level (food secure, mildly food insecure, moderately food insecure, and severely food insecure) and compared the proportions of crops grown in each group. To place households in these categories the following thresholds were used, which besides a scaling factor, mimic those used by Nsabuwera et al. 2015 who employed the HFIAS index to make inferences on food security in Rwanda:

> 36: Severely food insecure
18-36: Moderately food insecure
1-18: Mildly food insecure
0-1: Food secure

Results

Descriptive Statistics

To contextualize our findings, we first offer a quick profile of some key descriptive statistics:

In 9% of fields (n=216) some form of pesticide was applied in either the first or second round of data collection. Out of those pesticides, 91% were used to target insect & animal pests (n=196) while 4% were fungicides (n=9) and 5% were herbicides (n=11). Pesticide use varied by landscape and round, with the greatest amount used in landscape 3 in round 2, but none used in landscape 3 in round 1. The main crops that received pesticide application were cassava, maize, sweet potatoes, and Irish potatoes (*Appendix*, Figures A2.5, A2.6).

Organic fertilizers predominantly consisted of animal manure (97%), but also included crop residue (2%) and biomass transfer (>1%). 60% of fields used organic fertilizer in at least one round. Organic fertilizer was used by farmers in all landscapes in both rounds. The main crops that farmers applied organic fertilizer to included beans, maize, and Irish potatoes (*Appendix*, Figures A2.3, A2.4).

In 17% of fields, inorganic fertilizer was applied during at least one round. Inorganic fertilizer types used in our sample were primarily Di-Ammonium Phosphate (42%), Nitrogen Phosphate Potassium (40%), and Urea (17%). Primary crops that had application of inorganic fertilizer included Irish potatoes, tea, maize, and paddy rice (*Appendix*, Figures A2.1, A2.2).

For farmers who reported food loss for one or more of their crops, the primary reason for the loss was overwhelmingly rotting (60%), followed by insects (10.85%), flooding (9.95%), mammals (8.79%), and theft (4.65%) (*Appendix*, Figure A1.2).

Yield and Agricultural Practice

a) Mean Yield Comparison

At a .05 significance level, most plots applying a given strategy did not produce a greater yield in kilograms per hectare, though there were some exceptions.

First, fields that intercropped had a significantly different mean yield for the main crop on a field for beans, maize, and sorghum (Table 2.1).

Table 2.1. Welch's two-sample two-sided t-test results comparing reported mean yield harvest (kg) by cropping pattern (intercropped vs monocropped) and crop type.

Main crop	Mean yield (kg): Monocropped	Mean yield (kg): Intercropped	p-value
Banana Beer	9630.68	15563.67	0.160
Beans	769.54	671.74	**0.045**
Irish Potatoes	5170.80	5899.59	0.757
Maize	1299.07	908.95	**<.001**
Sorghum	1311.62	856.47	**0.033**
Soybeans	404.02	534.57	0.427

Plots which applied organic fertilizer had a significantly greater mean yield of Irish potatoes, bananas grown for beer, and beans out of the seven crops that were tested (Table 2.2).

Table 2.2. Welch's two-sample one-sided t-test results testing whether reported mean harvest (kg) of crops grown on plots which applied organic fertilizer were higher than plots which did not. This included all varieties of organic fertilizer.

Main Crop	Mean yield: No organic fertilizer	Mean yield: With organic fertilizer	p-value
Banana (beer)	8676.98	13991.59	**0.048**
Beans	672.50	767.99	**0.024**
Irish potatoes	3607.76	5616.30	**0.007**
Maize	1068.73	1227.84	0.084
Sorghum	1075.50	1391.89	0.122
Soybeans	368.81	607.81	0.090
Sweet potatoes	10330.65	8784.79	0.798

Only three crops had sufficient sample size to test for inorganic fertilizer, but mean yield was significantly greater for Irish potatoes and maize (Table 2.3).

Table 2.3. Welch's two-sample one-sided t-test results testing whether reported mean harvest (kg) of crops grown on plots which applied inorganic fertilizer were higher than plots which did not. This included all varieties of inorganic fertilizer.

Main crop	Mean yield: No inorganic fertilizer	Mean yield: With inorganic fertilizer	p-value
Beans	723.67	798.36	0.227
Irish Potatoes	546.44	1363.79	**<0.001**
Maize	1098.36	1420.76	**0.014**

For pesticide use, out of the three crops that had sufficient sample size, Irish potatoes and paddy rice exhibited a significantly greater mean yield (Table 2.4).

Table 2.4. Welch's two-sample one-sided t-test results testing whether reported mean harvest (kg) of crops grown on plots which applied pesticides were higher than plots which did not. This included all varieties of inorganic fertilizer.

Main crop	Mean yield: No pesticides	Mean yield: With pesticides	p-value
Irish potatoes	3454.86	6626.72	**<.001**
Maize	1190.42	995.31	0.866
Paddy rice	7398.25	12375.35	**0.014**

Erosion controls were positively associated with yield only for sorghum, out of four crops tested (Table 2.5). For use of improved seeds, out of six crops tested only soybeans were positively associated with yield (Table 2.6).

Table 2.5. Welch's two-sample one-sided t-test results testing whether reported mean harvest (kg) of crops grown on plots which employed erosion control were higher than plots which did not. This included all types of erosion control.

Main crop	Mean yield: No erosion control	Mean yield: With erosion control	p-value
Beans	723.67	798.36	0.227
Irish Potatoes	5170.80	5899.59	0.379
Maize	1299.071	908.95	0.999
Sorghum	1098.36	1420.76	**0.014**

Table 2.6. Welch's two-sample one-sided t-test results testing whether reported mean harvest (kg) of crops grown on plots which employed improved seeds were higher than plots which did not.

Main crop	Mean yield: No improved seeds	Mean yield: With improved seeds	p-value
Beans	780.99	664.70	0.992
Irish Potatoes	4513.80	5608.68	0.057
Maize	1174.93	1166.21	0.531
Paddy	9449.90	11171.55	0.340
Sorghum	1240.41	1149.41	0.636
Soybeans	1098.36	1420.76	**0.014**

b) Simple Clustered Linear Models

No significant associations were found between intercropping and yield for any of the crops in our sample. However, both Irish potatoes and bananas grown for beer may exhibit a positive correlation between intercropping and yield of these as a primary crop, as a strong positive association is well within the 95% confidence interval. Although negative correlations between intercropping and yield cannot be ruled out, no crops showed a significant negative correlation at a 95% confidence level. This results indicates some crops may be grown with a secondary crop on the field and still yield the same amount as that same crop would in a monoculture. That would make the yield of any secondary crop a bonus to the yield of the primary crop (Figure 2.1).

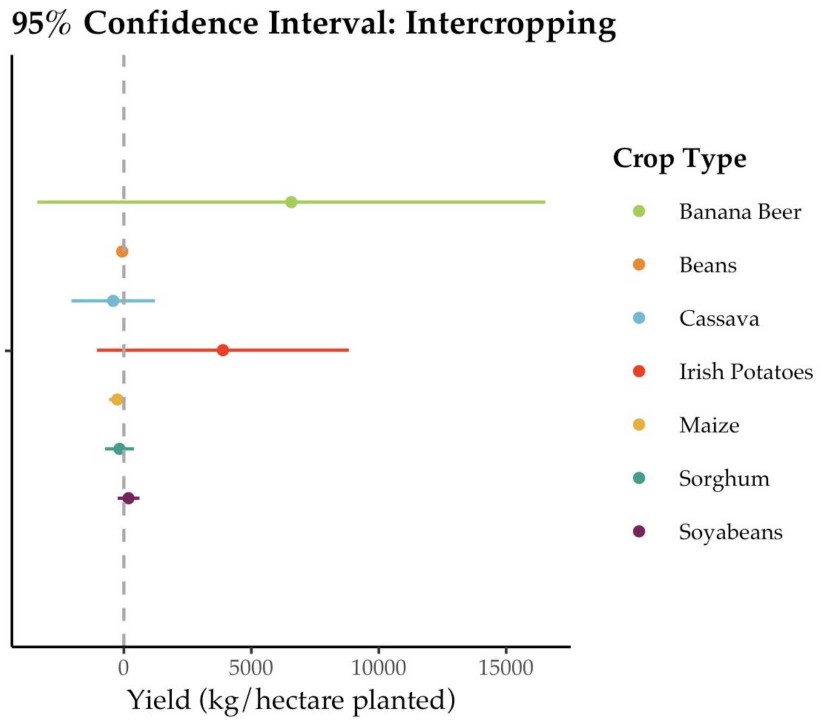

Figure 2.1. 95% confidence interval of linear model of harvest volume coefficients for intercropping. Each model was crop specific (each line corresponding to an independent model), controlled for Vital Signs landscape, round and season, and clustered standard errors on unique plot id.

Organic fertilizer use was not significantly associated with yield for any crop type. Irish potatoes may exhibit a small positive association, but a zero effect cannot be ruled out. Most crops exhibited something close to zero effect, but results for cassava and bananas for beer are rather inconclusive due to a wide confidence interval (Figure 2.2).

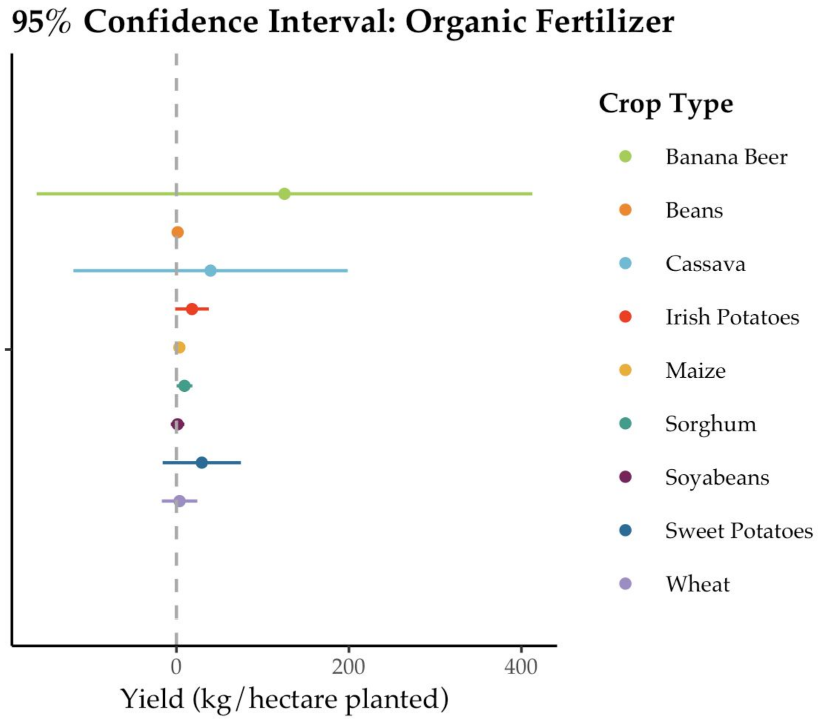

Figure 2.2. 95% confidence interval of linear model of harvest volume coefficients for the application of 100 kgs of organic fertilizer. Each model was crop specific (each line corresponding to an independent model), controlled for Vital Signs landscape, round and season, and clustered standard errors on unique plot id.

Inorganic fertilizer use was positively associated with significantly higher yield for Irish potatoes, maize, and wheat. Paddy may exhibit a positive association, but a zero or negative effect cannot be ruled out at a 95% confidence level. Results for sweet potatoes were inconclusive due to large confidence interval (Figure 2.3).

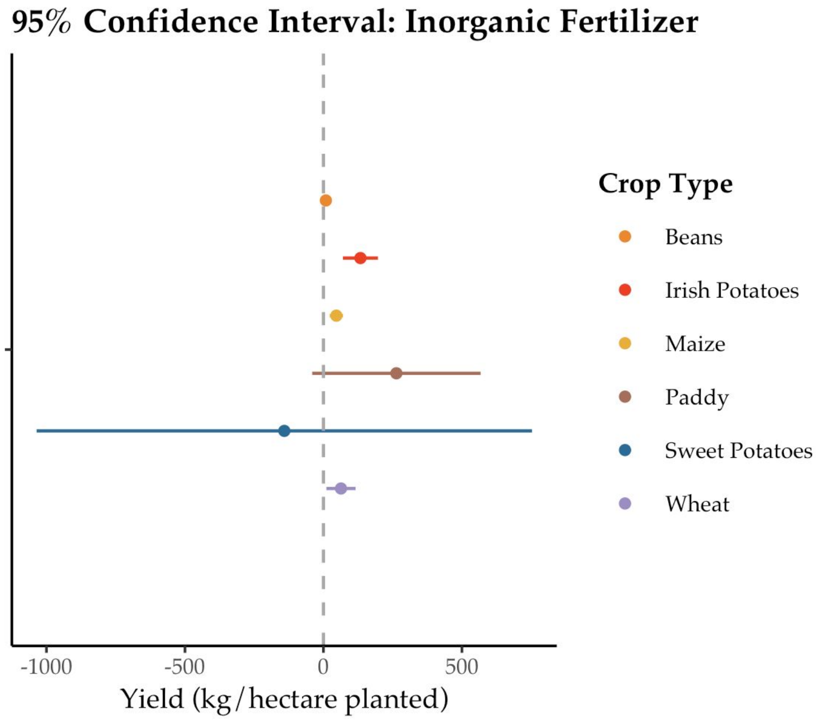

Figure 2.3. 95% confidence interval of linear model of harvest volume coefficients for the application of 10 kgs of inorganic fertilizer. Each model was crop specific (each line corresponding to an independent model), controlled for Vital Signs landscape, round and season, and clustered standard errors on unique plot id.

There were no significant results for use of pesticides, improved seeds, or erosion controls for yield. Many crops for each practice exhibited close to zero effect. However, paddy and sweet potatoes consistently exhibited wide error bars, and other crops showed wide error bars for only some practices (Figures 2.4 - 2.6).

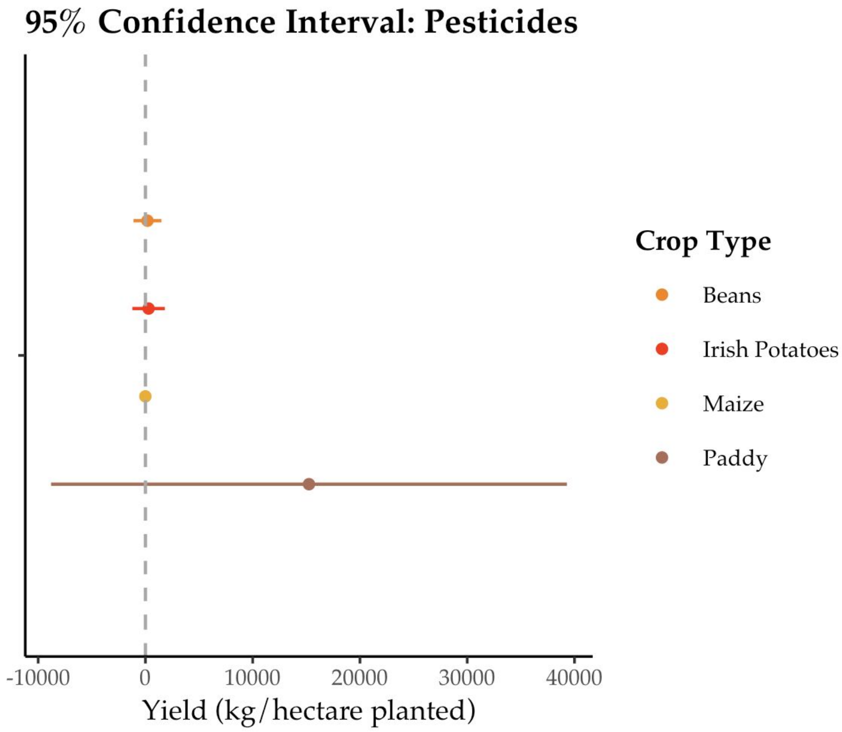

Figure 2.4. 95% confidence interval of linear model of harvest volume coefficients for the application of 10 kgs of pesticides. Each model was crop specific (each line corresponding to an independent model), controlled for Vital Signs landscape, round and season, and clustered standard errors on unique plot id.

The association between yield and pesticide use clustered near zero with relative certainty for tested crops, except for paddy which exhibited incredibly low confidence (Figure 2.4).

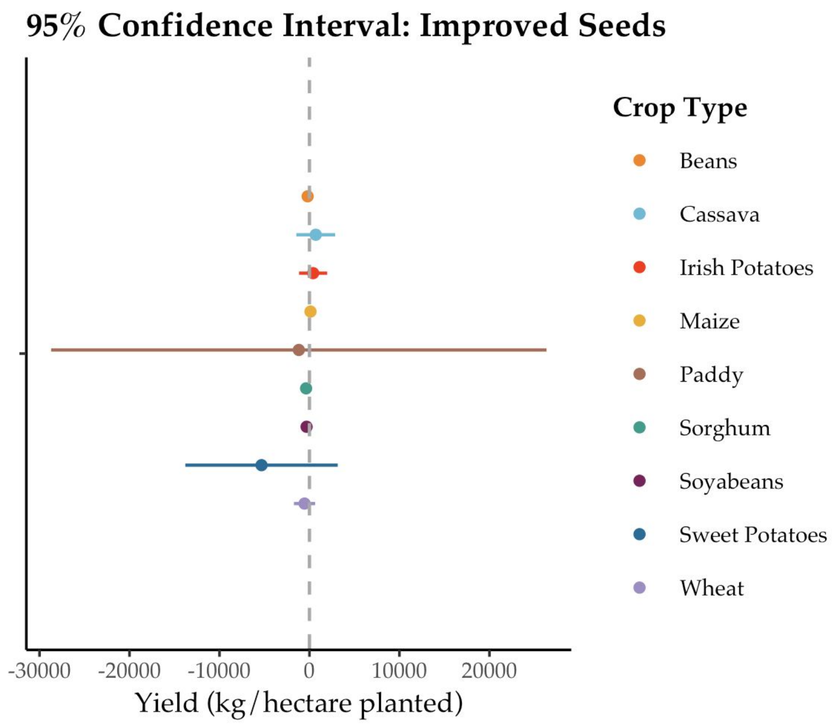

Figure 2.5. 95% confidence interval of linear model of harvest volume coefficients for the application of improved seeds. Each model was crop specific (each line corresponding to an independent model), controlled for Vital Signs landscape, round and season, and clustered standard errors on unique plot id.

The association between yield and use of improved seeds also clustered around zero with relative confidence for most crops, with paddy and sweet potatoes showing large levels of uncertainty (Figure 2.5).

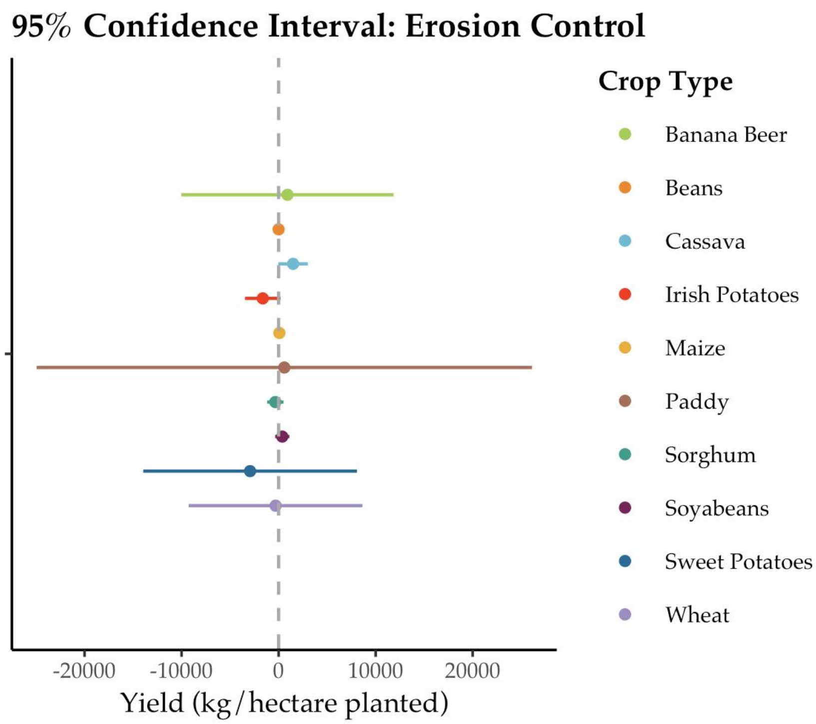

Figure 2.6. 95% confidence interval of linear model of harvest volume coefficients for use of erosion control. Each model was crop specific (each line corresponding to an independent model), controlled for Vital Signs landscape, round and season, and clustered standard errors on unique plot id.

The association between the use of erosion controls and yield also clustered around zero for most crops, but four of those crops showed large levels of uncertainty, again including both paddy and sweet potatoes (Figure 2.6).

c) Multiple Regression Models

In the multiple linear regression models, all agricultural practices were included in a single model of yield for each crop if there was sufficient sample size for that practice on that crop (n=5). Eight of the nine crops with largest sample size were analyzed: beans, Irish potatoes, maize, paddy rice, sorghum, soybeans, sweet potatoes, and wheat. Pyrethrum, with a sample size of 38, was not included as the quantity of its observations which received tested practices was severely limited. The results of a given practice varied by crop type, but most showing a non significant or close to zero effect of agricultural practices.

Both organic and inorganic fertilizer exhibited results with much greater certainty than other practices (narrower confidence intervals), though modeled effects of each of these clustered near zero for all crops. All other practices showed wide error bars in many cases, but this varied by crop (Figure 2.7).

Intercropping was positively associated with yield for Irish potatoes, soybeans, and wheat, but was significantly negatively associated with yield for maize. All other crops with sufficient sample size showed no significant association (Figure 2.7).

Erosion control was only significantly associated with yield for soybeans, for which the model shows a positive association. Most results were non-significant with great uncertainty, but erosion control was significantly negatively associated with yield for Irish potatoes and sorghum. (Figure 2.7).

Out of crops that had sufficient sample size, pesticide use was only significantly positively correlated with yield for paddy rice. The association for wheat was negative, although a zero effect cannot be ruled out. Irish potatoes and sorghum exhibit relatively precise zero effects (Figure 2.7).

Use of purchased seeds was significantly negatively associated with yield for beans and soybeans. All other crops showed no significant association, and sorghum and wheat showed relatively precise zero effects (Figure 2.7).

Multiple Linear Models

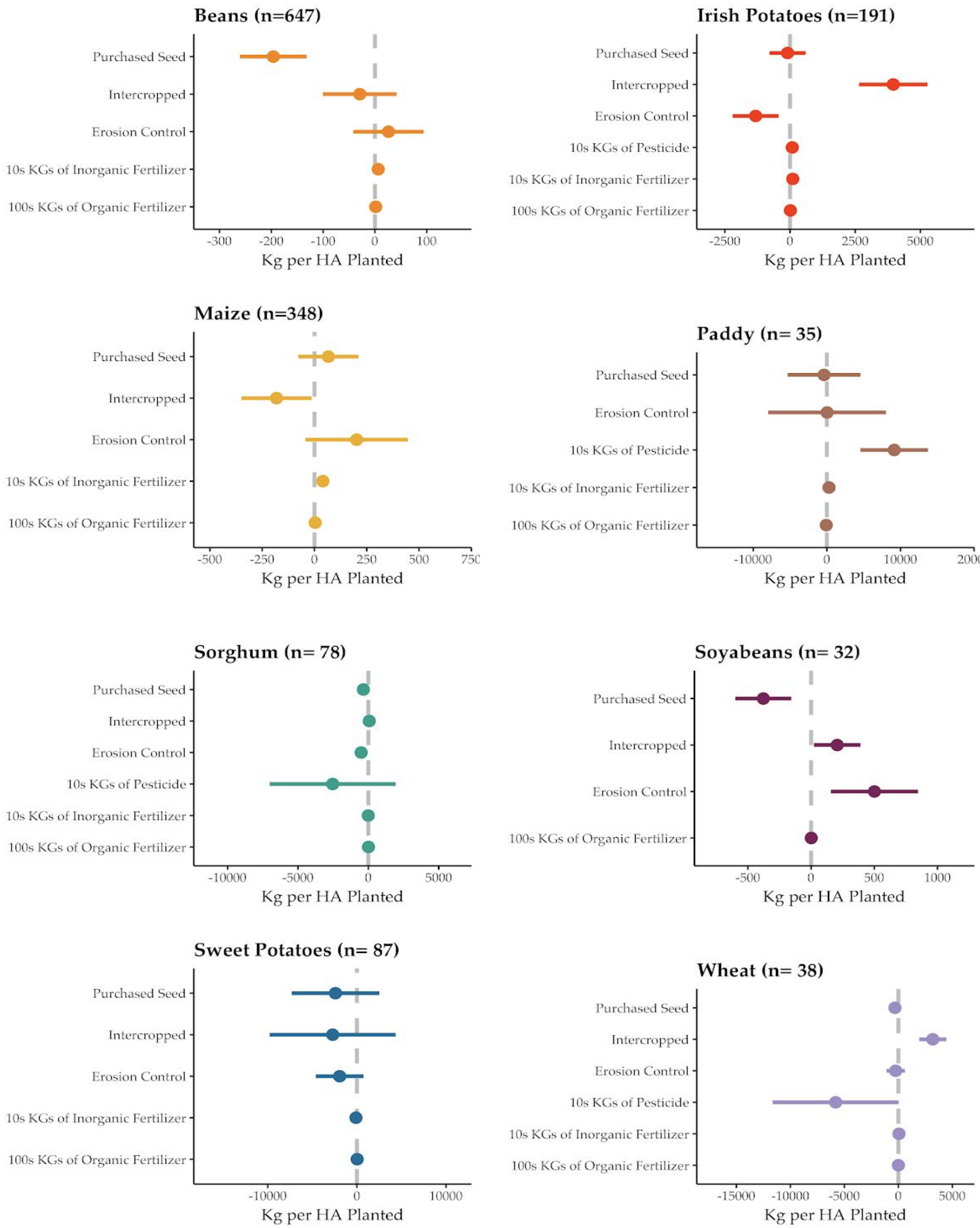

Figure 2.7. 95% confidence interval of multiple linear regression coefficients of yield volume for crops with greatest sample size. Each model controlled for Vital Signs landscape, round, and season, and clustered robust standard errors on unique plot id.

Yield Gap Analysis Results

The results of the yield gap analysis are summarized in Tables 3.1, 3.2, and 3.3 below. It is important to note that this analysis was intended to give an overall description of the differences in input use across crop types, and did not account for control variables such as landscape. Thus, these findings only inform broad patterns in the data rather than any causal relationship. With greater sample size, future analyses could possibly incorporate regional variations.

Results from a series of Welch's two-sample one-sided t-tests indicated a significant increase in mean inorganic fertilizer use (kg) in top yielding fields when compared to low yielding fields for Irish potatoes and maize (Table 3.1). On average, farmers in top-yielding groups for Irish potatoes and maize used 74.38% more inorganic fertilizer than farmers in low-yielding groups ($p<.001$). Beans and wheat also showed an increase in mean inorganic fertilizer use, though this increase was not significant.

Table 3.1. Results of Welch's two-sample one-sided t-tests comparing mean inorganic fertilizer use (kg) of top quartile of fields (high performers) and the lower three quartiles (low performers) by crop type.

Crop type	Mean inorganic fertilizer use (kg) in low yield group	Mean inorganic fertilizer use (kg) in high yield group	t-statistic	p-value	% Difference
Beans	10.08	12.14	-0.463	0.321	16.97%
Irish potatoes	71.23	285.64	-6.455	**<.001**	75.06%
Maize	16.79	63.85	-3.376	**<.001**	73.70%
Wheat	59.86	179.23	-1.288	0.114	66.60%
				Average of Significant Values	74.38%

For all crops with sufficient sample size to be tested, fields in the high yield group received on average more inorganic fertilizer than in the low yield group. These results were significant for two out of the four crops (Table 3.1).

A series of Welch's two-sample one-sided t-tests indicated a significant increase in mean organic fertilizer use (kg) between top yielding and low yielding fields for beans, Irish potatoes, maize, soybeans, and sweet potatoes (Table 3.2). Mean organic fertilizer use was on average 72.94% higher in top-yielding fields that showed a significant difference. Organic fertilizer use was also higher for crop types including bananas (beer), cassava, and sweet potatoes, though this increase was not significant.

Table 3.2. Results of Welch's two-sample one-sided t-tests comparing mean organic fertilizer use (kg) of top quartile of fields (high performers) and the lower three quartiles (low performers) by crop type.

Crop type	Mean organic fertilizer use (kg) in low yield group	Mean organic fertilizer use (kg) in high yield group	t-statistic	p-value	% Difference
Banana (beer)	3520.17	5315.92	-1.101	0.141	33.78%
Beans	3092.06	8152.28	-3.196	**<0.001**	**62.07%**
Cassava	978.58	1204.79	-0.339	0.369	18.78%
Irish potatoes	5335.33	11473.89	-1.825	**0.036**	**53.50%**
Maize	2333.59	8221.00	-2.292	**0.012**	**71.61%**
Sorghum	915.64	5814.49	-2.875	**0.004**	**84.25%**
Soybeans	1181.5	17485.37	-1.943	**0.042**	**93.24%**
Sweet potatoes	10405.52	30689.39	-1.523	0.070	66.09%
				Average of Significant Values	72.94%

For all tested crops, fields in the high yield group also received, on average, more organic fertilizer than in the low yield group. These results were significant for over half of tested crops (Table 3.2).

There was no significant increase in pesticide use found between the high and low performing groups for any of the crops tested, including beans, Irish potatoes, maize, and paddy rice (Table 3.3). For Irish potatoes and paddy rice, pesticide use was higher in the high yield group, while for beans and maize pesticide use was lower in the high yield group. All p-values were greater than .05.

Table 3.3. Results of Welch's two-sample one-sided t-tests comparing mean pesticide use (kg) of top quartile of fields (high performers) and the lower three quartiles (low performers) by crop type.

Crop type	Mean pesticide use (kg) in low yield group	Mean pesticide use (kg) in high yield group	t-statistic	p-value	% Difference
Beans	15.35	0.26	0.990	0.838	-5803.85%
Irish Potatoes	21.74	198.67	-1.086	0.141	89.06%
Maize	5.85	0.60	1.470	0.930	-875.00%
Paddy	.43	4.34	-1.69	.065	90.09%

For crops with sufficient sample size to be tested, mean use of pesticides was greater in the high yielding group for only two out of four crops, and none of these results were significant (Table 3.3).

Food Security Analysis Results

Simple linear models were run on household food security index score as a function of agricultural intervention (inorganic fertilizer, organic fertilizer, pesticides, intercropping, and erosion control) with Vital Signs landscape as a control variable. We were unable to control for individual household income due to data missingness, as only 20 out of 280 households had a reported value for household income. Because household income is likely among the strongest contributors to household food security, this was an analysis limitation. We can logically assume that households with greater income purchase more food and more agricultural inputs such as fertilizers and pesticides. This likely partly accounts for some of the association between fertilizer or pesticide use and household food security.

At a .05 alpha level, households that used inorganic fertilizer, used pesticides, or intercropped were each significantly more food secure than households that did not (Figures 4.2-4.3). Households that used organic fertilizer or employed erosion control techniques were also more food secure than households that did not, but the results were not significant at the 0.05 level.

Households that used inorganic fertilizer were significantly more food secure than households that did not ($p < .001$). Mean index score was 4.3 points lower for households that used inorganic fertilizer (Figure 4.1).

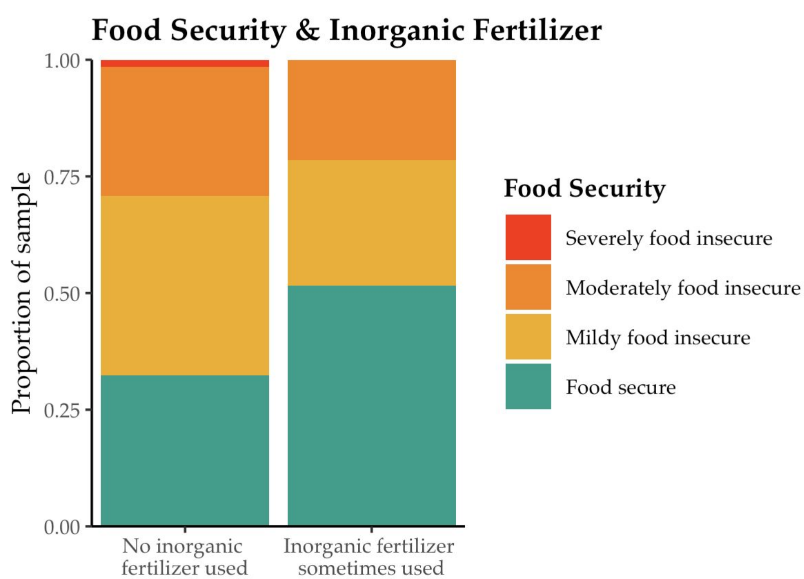

Figure 4.2. Stacked bar chart of household food insecurity levels for households that did not use inorganic fertilizer (left) and those that did use inorganic fertilizer (right).

Households that used pesticides were significantly more food secure than households that did not (p = .023). Mean index score was 3.1 points lower for household that used pesticides (Figure 4.2).

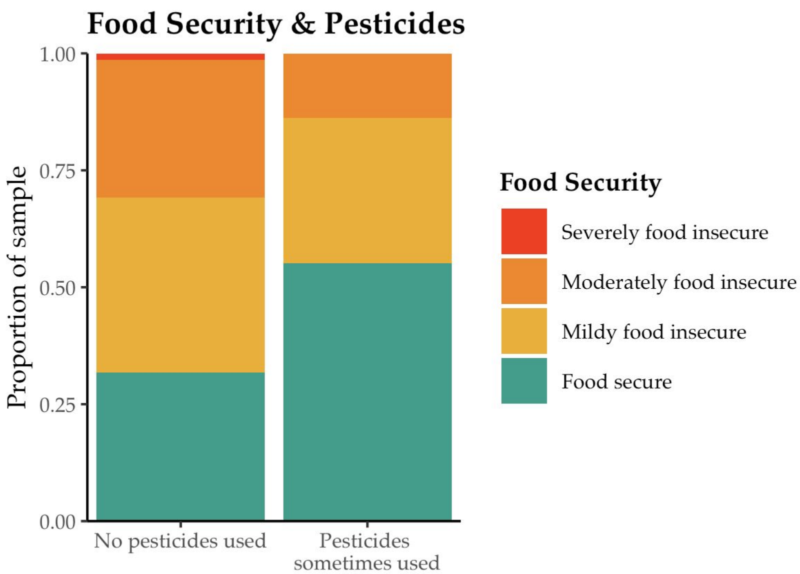

Figure 4.3. Stacked bar chart of household food insecurity levels for households that did not use pesticides (left) and those that did use pesticides (right).

Households that intercropped were significantly more food secure than households that did not (p = .036). Mean index score was 2.5 points lower for these households (Figure 4.3).

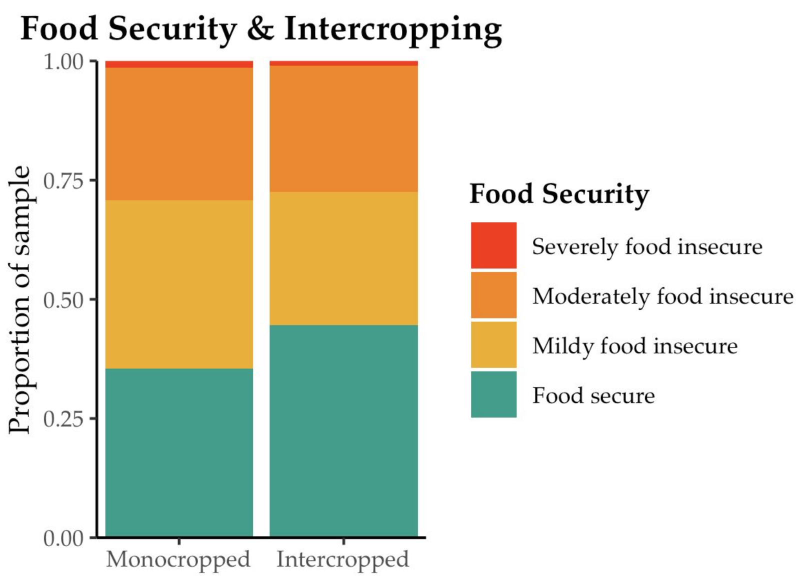

Figure 4.3. Stacked bar chart of household food insecurity levels for households that monocropped (left) and households that intercropped (right).

Food security varied across landscapes (Figure 4.4). Landscape 12 was most food secure followed by landscapes 2 and 3. Landscape 11 was by far the least food secure, followed by landscape 1, 4, and 7.

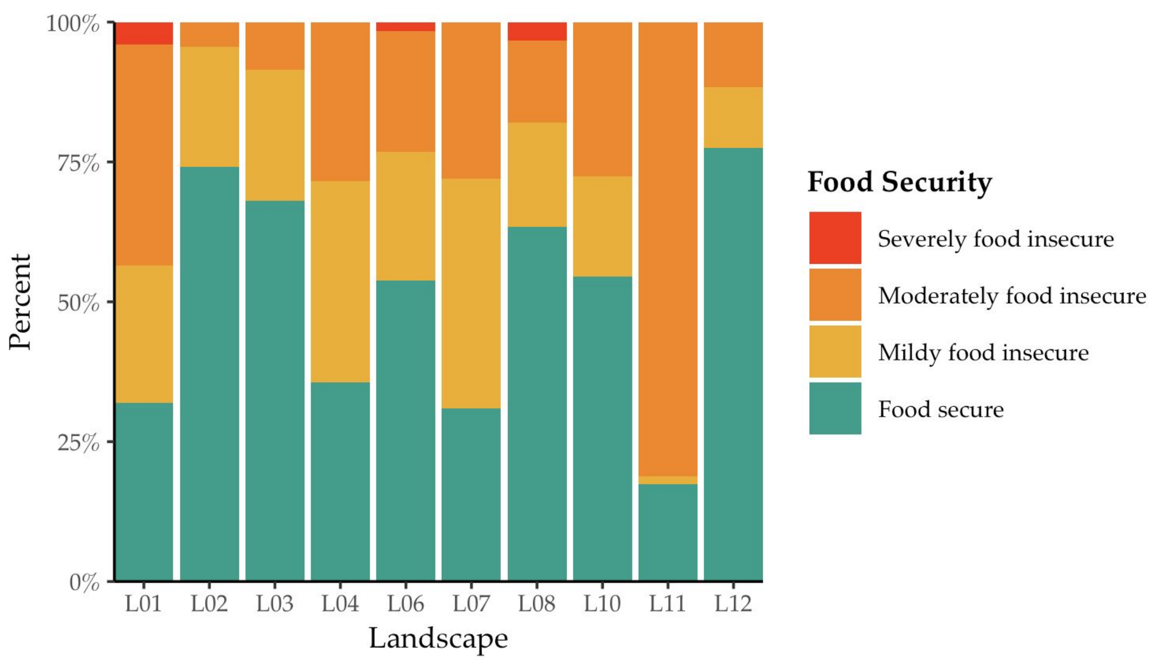

Figure 4.4 Food security by landscape. Color indicates food security level, scored from food secure to severely food insecure.

Our comparison of the different crop types grown by farmers in the four levels of food security on the index scale (food secure (n=145), mildly food insecure (n=110), moderately food insecure (n=96), and severely food insecure (n=4)) determined that a different variety of crop types are grown by farmers at varying levels of food security. In terms of subsistence crops, groundnut, sweet potatoes and yams were grown more frequently by farmers in the severely food insecure group than by farmers in the food secure, mildly food insecure, and moderately food insecure group. Wheat was grown more frequently both in severely and moderately food insecure groups than in the mildly food insecure and food secure groups. Alternately, bananas (grown for both food and beer) and sorghum were not grown at all by farmers in the severely food insecure group, but grown only by farmers that were food secure, mildly food insecure, and moderately food insecure. All groups predominantly grew beans (lower in the severely food insecure group), Irish potatoes, and maize (Figure 4.5).

Commodity crops in our sample include coffee, tea, and pyrethrum. Coffee was grown by farmers across all levels of food security, but was more prevalent in the groups of farmers who are severely food insecure. Alternately, pyrethrum is primarily grown by farmers who are food secure, with a small proportion also grown by farmers who are mildly food insecure. Finally, tea was grown across food secure, mildly food insecure, and moderately food secure groups, with the largest proportion grown in the moderately food insecure group (Figure 4.5).

It was difficult to discern patterns for any other crops due to the low sample size. There is also a much lower diversity in the crop types grown in the severely food insecure group when compared to the food secure groups. However, this is likely largely a function of sample size as the severely food insecure group had only 4 households in the sample (Figure 4.5).

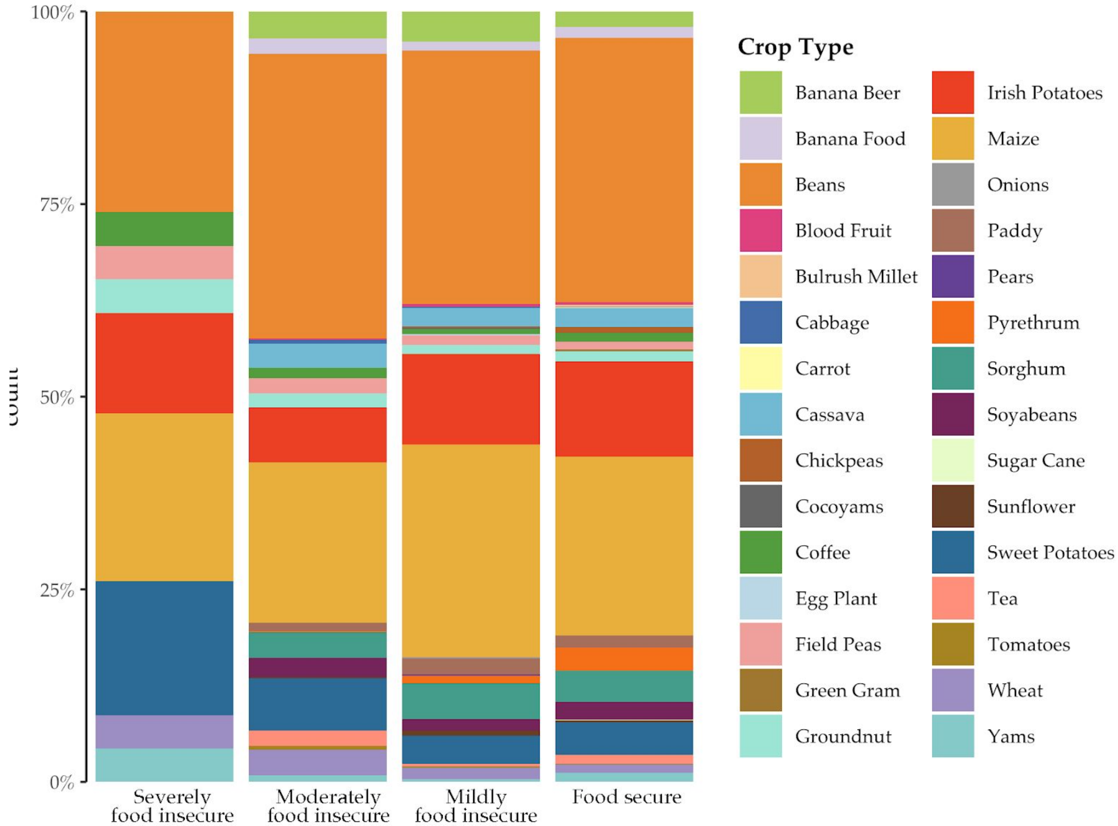

Figure 4.5. Distribution of crop types grown across food security levels. Crop types grown in households that are food secure, mildly food insecure, moderately food insecure, and severely food insecure.

Recommendations

Data Recommendations

If Conservation International wishes to answer key questions about sustainable agricultural production and smallholder food security, we recommend a number of changes to the Vital Signs data collection protocols in future rounds of data collection.

With limited resources, it is important that Vital Signs prioritize sampling and survey questions based on the most likely use cases for the data. We will provide recommendations under the assumption that the main use case is to inform the agricultural management decisions of policy makers, extension agents, and smallholder farmers to intensify production sustainably and improve household food security. The following recommendations can be adapted to whatever use case the client designates to be the priority.

Table 4.1. Data limitations, examples of those limitations, and recommendations to address those limitations.

Limitation	Example	Recommendations
Insufficient sample for some questions	Over half of crops have sample size of $n<15$.	Change sampling strategy based on indicators most relevant to the use case.
Survey questions inconsistent with desired analyses	Food security questions only cover one of four pillars of food security.	Select survey questions based on planned analyses. Remove extraneous questions.
Data quality concerns	Household income only reported for 20 of 280 households. Outliers for yield and input use, for example with maize and Irish potatoes. Unclear whether these values are errors.	1. Incorporate verification criteria into data collection protocol to protect against inaccurate reporting or recording. 2. Add questions which speak to how long a farmer has employed a given agricultural practice.
Longer term monitoring of same households (only two rounds complete)	Only two rounds of data collection for only part of the sample, over a very short time span (~1 year).	Continue future rounds of VS data collection with sufficient frequency for panel data analysis.

Currently, Vital Signs is incredibly broad in the types of indicators that it covers, but shallow in its sample size. Sample size proved to be the most limiting aspect of analysis, particularly once data was disaggregated by landscape, crop type, or agricultural practice. Only 15 of 30 crop types exhibited a sample size greater than 30. Increasing sample size can be very resource intensive. Therefore, we recommend that sample size be expanded strategically based on the research questions that are most relevant to the use case. If the goal is to examine the relationship between agricultural practices and yield or food security, then sampling should be expanded to include more households that enact these practices. This may mean expanding the total number of households surveyed. The added cost and time requirement might be mitigated by surveying less frequently or using a shortened survey.

An additional issue was that the selection of survey questions did not always match the desired analyses. Many of the survey questions may not be relevant to the main use case of the data, while certain questions may be missing that would improve the robustness of the results. For example, food security can be measured on four pillars: availability, access, utilization, and stability (FAO 2008). However, the food security index used for analysis Vital Signs data set was only able to address the access pillar of food security because there were not questions in the survey that could speak to the other three pillars. If Vital Signs wishes to produce a more robust food security index, it may be beneficial to include questions that can address all four pillars. It would also be beneficial to include questions of how long farmers have enacted a particular agricultural practice, as some practice may take multiple seasons to accrue benefits.

Data quality was also an issue as unexpected outliers, variance, and data missingness were common. For example, out of 280 total households, only 20 reported a value for household income. As an additional example, kilograms of yield reported for a given field in a given season showed unusual outliers for numerous crop types such as maize and Irish potatoes. Under the current system of protocols, it is difficult to discern whether unusual outliers or variance are errors. If they are errors, it is unclear whether they are errors in reporting on the part of the respondent, or errors in recording on the part of the data collector. This makes it difficult to determine how to address these values.

While statistical methods can be used to address these issues during analysis, more verification criteria could be built into the Vital Signs protocol to protect against errors during data collection. This would strengthen the data and minimize data loss, which is particularly key with a limited sample size. For example, to address outliers and variance thresholds can be established for the maximum and minimum values that would be expected for a given indicator. If a value is recorded outside of that threshold, it should be flagged and possibly investigated further by the data collector through follow up questions with survey respondents. Some indicators that may most benefit from this include yield by both kilograms and Rwandan francs, and the amount of inputs used (i.e. fertilizers and pesticides). To address data missingness, if no value is reported for a given survey question, a follow up explanation should be provided as to why. Did the respondent choose not to answer for a specific reason? Did they not know the answer to the question? Was the data collector unable to reach the respondent? Or was the data simply lost during processing? This will help data analysts determine whether the missingness was random to better select the appropriate statistical analyses. It will also help identify issues with data collection that it may be possible to address.

Vital Signs was designed to produce a panel data set and continuing to build the panel through future rounds of data collection will improve the data's ability to causally answer questions such as those addressed in this report. This requires a sufficient sample size to account for any attrition that may occur over the course of repeated samplings. Both producing this sample size and repeated resampling of households would be time and resource intensive. One way to reduce costs may be to sample more infrequently. Similar panel data sets of smallholder household surveys sampled every three years. Sampling only occurred two to four times in these cases, and attrition ranged from 18% to 26% over those periods (Katengeza et al. 2019; Abro et al. 2018; Sauer et al. 2018). For Vital Signs, attrition between the two rounds of data collection (approximately one year apart) was small, at no more than 7%, but it is unknown how this may increase over multiple years of sampling. Despite this uncertainty, we assert that producing a complete panel data set will improve the Vital Signs data's ability to inform agricultural management decisions in a meaningful way.

Agricultural Management Considerations

Results regarding the relationship between agricultural practices and yield varied by practice and crop type. This suggests agricultural management recommendations will be most effective when they are tailored to specific crops, and should consult analyses on the efficacy of practices concerning each individually.

Broadly, the use of inputs such as organic and inorganic fertilizers, pesticides, and improved seeds were not associated with statistically significantly greater yields across crops. However, there were some exceptions, and further, analysis of the yield gap did show in a somewhat contradictory manner that top performers are still using more of these inputs. Finally, some inputs were associated with greater household food security, although this is likely confounded by household income, presumably a strong predictor of household food security and input access and for which data was too limited to add a control. The result of intercropping being associated with greater food security is perhaps the most interesting, as this is not a strategy which requires purchasing inputs such as fertilizers and pesticides, and literature does suggest intercropping can reduce interannual variance in yield which could be reasoned to provide a slow accruing food security benefit (Dallimer et al. 2018; Swanepoel et al. 2018; Himmelstein et al. 2017; Brooker et al. 2015, Snapp et al. 2010). Further, intercropping was seldom associated with significantly lower yield of a given primary crop, again suggesting there may be a benefit to the practice in the form of a secondary crops harvest. Maize was one exception to this pattern (table 2.1; figure 2.7). If continued research aligns with the results of this project, then a future recommendation may be to promote intercropping as a means of increasing yield and household food security, for all crops except maize.. This would likely occur at the regional extension officer level.

Use of pesticides, improved seeds, and erosion controls all showed varied results when compared to yield depending on crop type. Some crops showed a positive association, some negative, but most showed no significant result. The lack of association found in these results seems counterintuitive to conventional knowledge, and warrants further investigation to confirm if there truly is or is not a relationship between application of these inputs and yield.

Our results may partially be a product of limited sample size, or because inputs were applied incorrectly. If further analysis find similar trends to those identified here, agricultural managers should focus efforts on appropriate training for the correct timing and specific use of these inputs, as these are key to maximizing their theoretical benefits (Tilman 2011). The Vital Signs data cannot speak to the current timing or rate of input application, and this warrants further investigation.

The Vital Signs data also cannot speak to why fertilizer use is so low. The government currently provides subsidized inorganic fertilizer through regional extension services which partner with private fertilizer distributors. However, Nahayo et al. found that farmers' use of subsidized fertilizers was hindered by poor distribution of fertilizer, with inadequate amounts and late deliveries. They also found that use of inputs including fertilizer was linked to non-farm income, which suggests that the cost of inputs may still be a barrier, despite subsidies (Nahayo et al. 2017). Vital Signs data might benefit from survey questions asking why farmers do or do not use fertilizers to help corroborate potential barriers to use. Extension services programs can then be altered to address those specific barriers.

Environmental and Policy Implications

Environmental Impacts

It is critical to consider the potential environmental impacts of various agricultural management decisions, and forecast changes in farm inputs, land use and agricultural intensity. If the tentative patterns found in our results hold with further research, then there are a number of key takeaways and considerations for decision makers.

Increased use of inorganic fertilizers may pose a risk to water quality, which is harmful to both the ecosystem and humans who depend on these water sources. When fertilizers are overused or used at incorrect times crops cannot uptake all nutrients, which then run off into waterways. Nutrient overload in rivers is known to perturb the ecosystem and affects the balance between and types of species that grow in native vegetation. Runoff also leads to eutrophication, killing fish and altering aquatic ecosystems (Clay et al. 1995). Nutrient overload also decreases the safety of drinking water. However, different inputs result in different outcomes. For example, excess nitrogen in drinking water affects digestive processes, hemoglobin and blood oxygen transport and has carcinogenic effects. All of these health effects are more dangerous for children and the elderly (Savci 2012).

This harm can be mitigated by applying the correct amounts of fertilizer at the correct rate and time to ensure maximum uptake of nutrients by crops and minimal runoff into waterways (Tilman 2011). Proper planning of input application can also improve efficiency of use, meaning farmers spend less money on inputs for the same benefits to yields. This may allow some farms to overcome cost barriers to using fertilizer. Extension services would need to provide training to fertilizer recipients to ensure that they are aware of best practices for fertilizer application in addition to providing the correct amount of subsidized fertilizer in a timely fashion, which the program already struggles with (Nahayo et al. 2017).

If intercropping is found to increase the total amount of food grown on a plot and increase food security, then it may provide a sustainable way to intensify agriculture that can also provide ecological benefits. Intercropping has been associated with reduced soil erosion and increased nutrient uptake. This means less sediment and nutrient runoff to waterways, which protects water quality (Clay et al. 1995). This may reduce the need for erosion control or for ecologically harmful inputs like fertilizer. It also reduces the pressure to extensify, or expand land cover for agriculture. Reducing this pressure is key to protecting the few ecologically critical habitats that remain uncultivated in Rwanda, and the biodiversity that they support.

The benefits of intercropping remain somewhat unclear and may be specific to certain crops or landscapes (Swanepoel et al. 2018). Therefore it may not be viable for all farmers to participate in intercropping. It may also require increased labor or additional seeds, which can be barriers to implementation. Theses are all tradeoffs that decision makers must consider, and partly why further research on the crop- and landscape-specific consequences of intercropping are necessary.

Under the assumption that farmers will eventually switch to the crop types and agricultural practices that provide the greatest value, we can make some predictions about what crops and associated practices may be adopted in a given landscape over time. We can then infer the potential environmental impacts that ecosystems would face as a consequence of that switch. However when considering these potential impacts, we must take into consideration that they are based on an assumption that crop choice is not linked to other factors such as the cultural value of certain crops or family tradition of growing the same crop over generations. Thus any predictions and their associated implications should be considered carefully.

Interestingly, commodity crops (tea, coffee, and pyrethrum) were infrequently present as one of the top three most valuable crops in a given landscape (Table A1.1). This may be because they are simply not present in some landscapes, and tied to the low sample size, but it demonstrates that these commercial crops may not be the best value for smallholder farmers. Another notable result of the analysis on crop value by landscape was that Irish potatoes were one of the top three most valuable crops in half of the landscapes in our sample (Table A1.1). According to our dataset, Irish potatoes use more inorganic fertilizer and pesticides per hectare than any other crop, and more organic fertilizer per hectare than the majority of crops (other than field peas and maize). This indicates that if there were to be an increased adoption of growing Irish potatoes in landscapes in which they are most valuable, we can expect an increase in the use of pesticides and fertilizer. These increases would pose a risk to groundwater quality and ecosystem health due to runoff in those landscape if mitigation measures are not taken. This is especially true if farmers are not trained on efficiency in the timing, rate, and amount of input application for maximum crop uptake.

Policy Implications

There are also numerous policy considerations for decision makers if they were to implement any agricultural management recommendations that might be suggested through further research. Some policies and programs already exist that seek to improve smallholder yield and household food security. These policies may provide pre-existing frameworks for the implementation of project recommendations or may provide a hindrance.

The Rwandan government has already enacted a number of policies in an attempt to increase farmer access to modern inputs, namely inorganic fertilizers, in an effort to modernize and intensify the agricultural sector. The Crop Intensification Program (CIP) promotes smallholder access to inorganic fertilizers through district-level extension service providers, which partner with private distributors to supply fertilizer at a subsidized price. As discussed, assuming that fertilizers are positively associated with yield, the program in its current form is likely not enough. Increasing access means reexamining the current extension service program and identifying ways to increase the amount and improve the timing of fertilizer delivery. This may mean increasing government funding to increase the amount of subsidized fertilizer and to lower the cost barrier. It may also mean improving distribution channels to ensure fertilizer arrives at the correct time. This would include improving infrastructure such as roads and increasing farmer participation so that fertilizers can be delivered in accordance with growing schedules.

While organic fertilizers were not often associated with higher yields in our results, we can still consider the policy implications if these inputs were timed correctly, and able to work as well as possible . The only program that currently supplies organic fertilizer is the One Cow per Poor Family Program, or Girinka Program. This program provides dairy cows to low income households primarily to address food insecurity through meat and milk production. Organic fertilizer is a byproduct, but is intended as an added bonus for farming. Literature indicates that Girinka participation is positively associated with farm yield, which may be due to the additional fertilizer source (Paul et al. 2018). Decision makers may wish to consider whether it would be more effective to incorporate increased organic fertilizer access into the CIP or expand it within the Girinka Program. Girinka participants reported difficulty with transporting manure due to a lack of tools, so this may be an additional avenue for increasing organic fertilizer use (Kim et al. 2013).

Current Rwandan government policy does not promote intercropping as a means of increasing yield or food security. Programs encourage monoculture and consolidation of small farms as a means of achieving the Vision 2020 agricultural goals. The CIP promotes the consolidation of smallholder plots and encourages all farmers in a given region to grow the same crop type (MINAGRI 2011). Intercropping is not promoted as a means of increasing yield or food security. There is evidence that this current strategy leaves the poorest farmers behind, and exposes smallholders to risk should a crop fail or market prices fall. Overall, while the CIP's monocropping strategy might increase overall yield in some cases, it may exacerbate food and economic insecurity, and lacks the environmental benefits linked to intercropping (Clay 2017, Nahayo et al. 2017, Cioffo et al. 2016). Because the government's policies are focused on monoculture, intercropping may not fit the government's vision of a consolidated agricultural sector. Therefore the idea of intercropping may meet resistance. However, this resistance may be overcome by emphasizing to decision makers the potential costs and benefits to the environment and household food and economic security of intercropping versus monocropping.

Conclusion

As populations continue to grow in the coming decades, so too will agricultural production and subsequent pressure on ecosystems. This is particularly true in sub-Saharan African nations like Rwanda, where populations are dense, most citizens are smallholder farmers, and land competition is mounting. However, with the right information, agricultural development decision makers can design solutions that maximize yields and protect food security while reducing the ecological impacts of farming. Vital Signs seeks to meet this need for information.

This project analyzed the Vital Signs data set to explore the relationships between agricultural practices, yield, food security, and the environment in Rwanda. The project also tested the ability of the data set to speak to these relationships, and identified limitations to the robustness of the data. Based on these results, a number of recommendations were made regarding ways to strengthen the data set and improve data collection protocols going forward. The project found some mixed results surrounding the relationships between agricultural practices and yield or food security, though highlights opportunities for developing intercropping as a pathway to bettering food security and sustainable intensification.

Vital Signs is a unique data set in its scale and integration of data across disciplines. Although further data collection and analysis is needed to ensure that it can answer important questions about sustainable agriculture. Decision makers will need to weigh the synergies and tradeoffs of different agricultural management decisions as they seek to maximize production, feed people, and minimize ecological harm. With improvements like those recommended in this report, Vital Signs could be a powerful tool for decision makers as they weigh these choices in the future.

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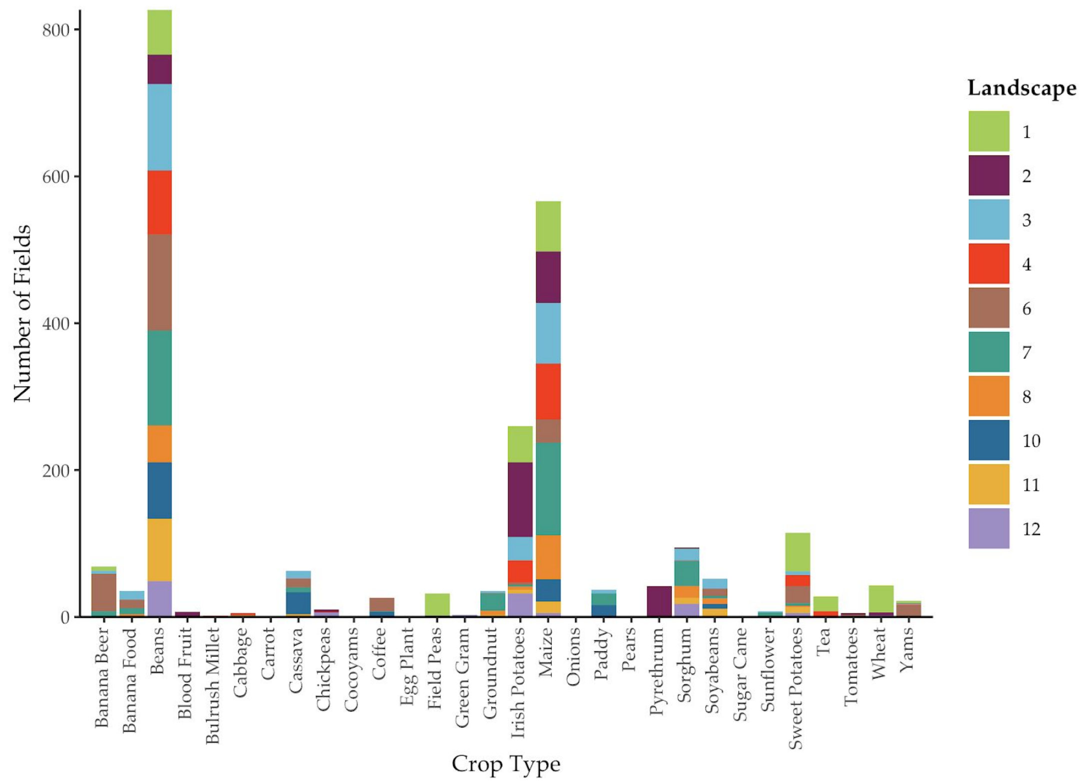

Figure A1.1 Crop type grown across fields in our study. Count of fields growing each crop type across each of 10 landscapes.

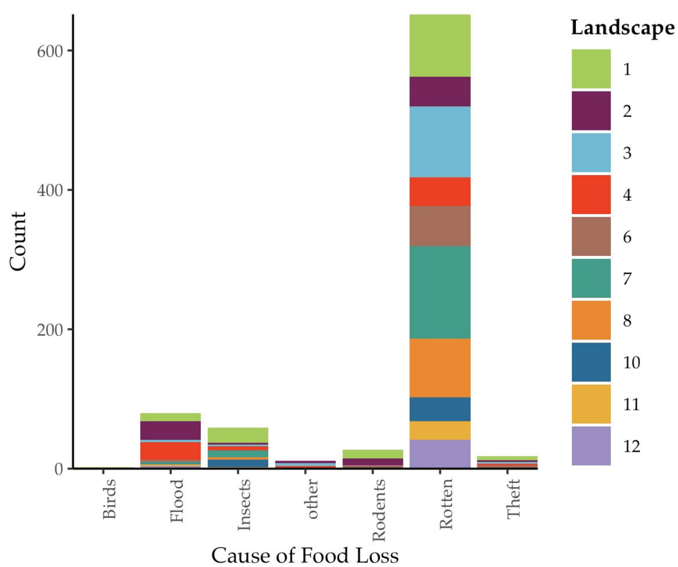

Figure A1.2 Cause of post-harvest food loss by landscape. Color indicates landscape, and count indicates number of respondents.

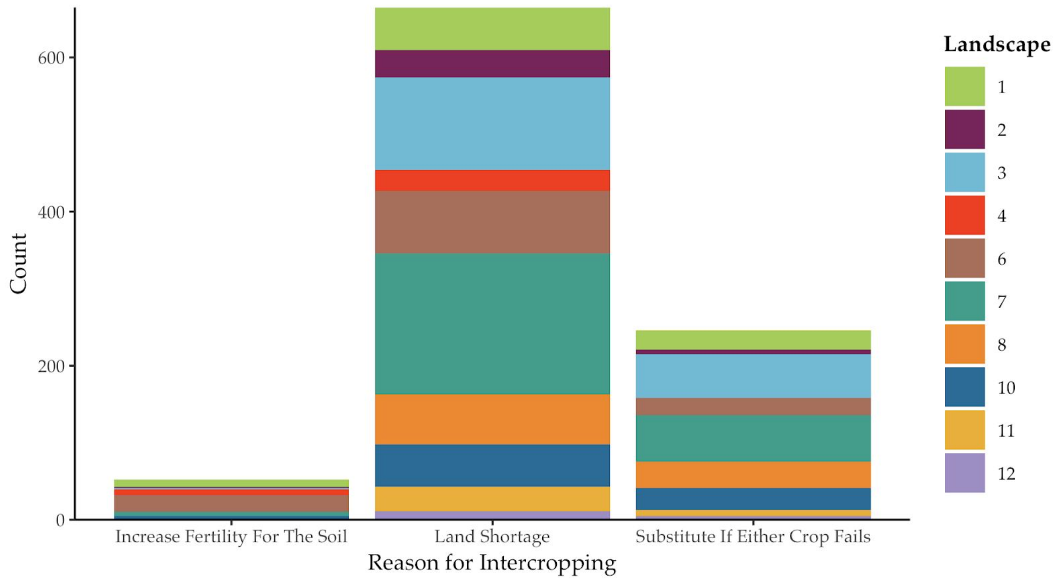

Figure A1.3 Reported reason for intercropping by landscape. Color indicates landscape number and count indicates number of respondents.

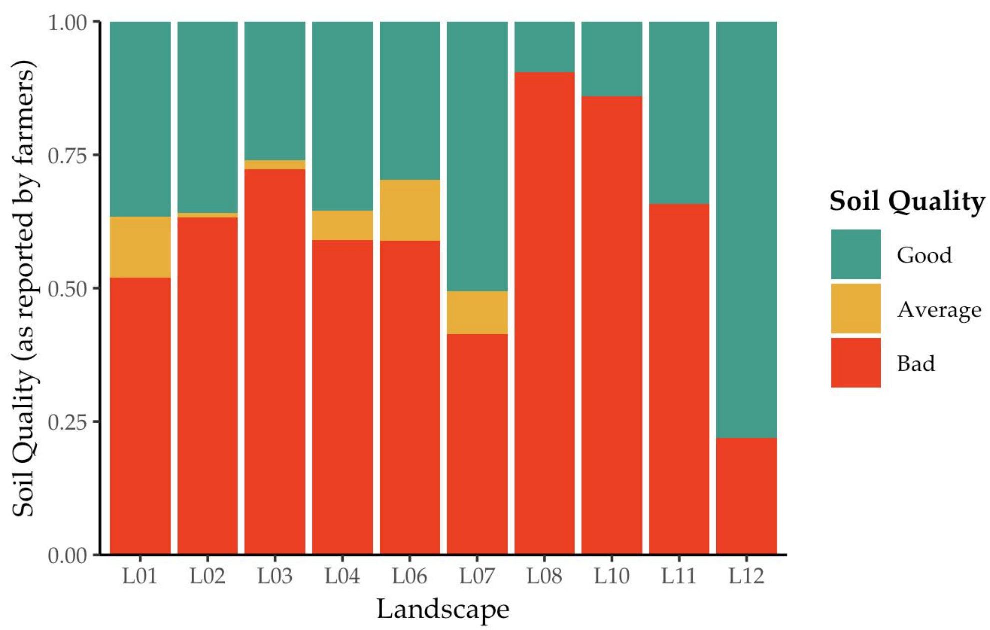

Figure A1.4 Reported soil quality by landscape. Color indicates soil quality, scored from good to average to bad.

Inorganic Fertilizer

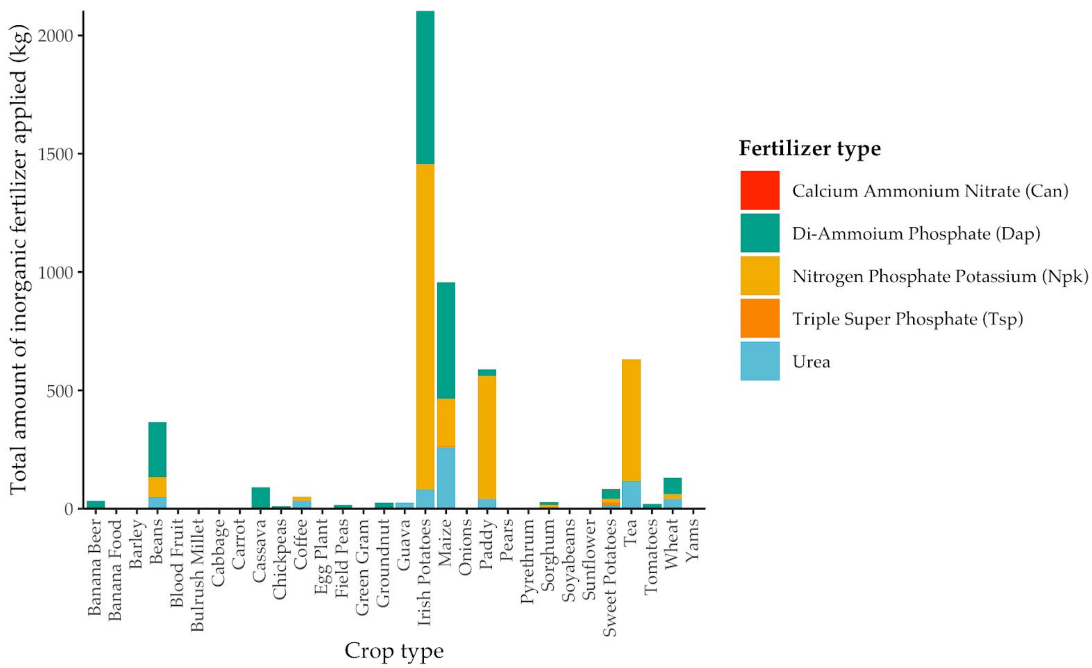

Figure A2.1 Total use of inorganic fertilizer (kg) by crop type over all landscapes and both rounds of data collection.

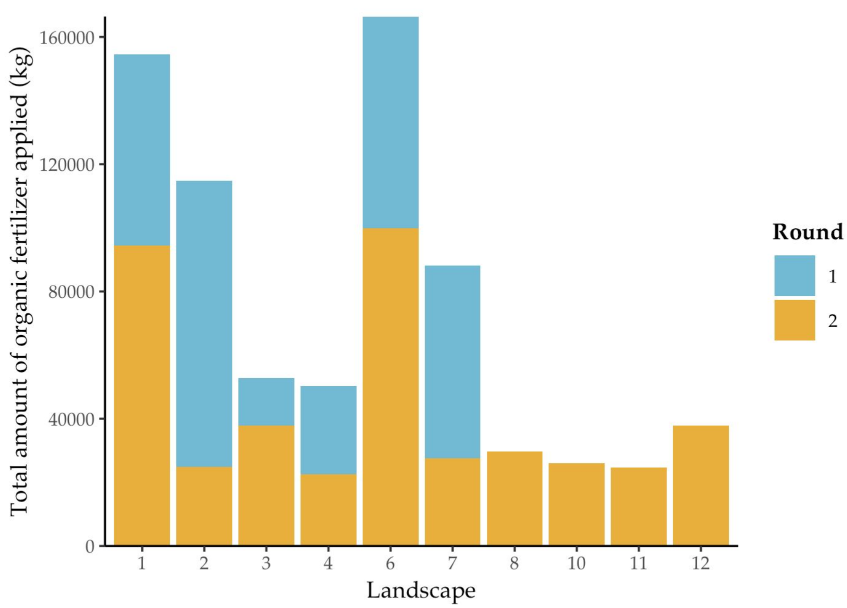

Figure A2.2 Total amount of inorganic fertilizer (kg) applied by landscape and round of data collection

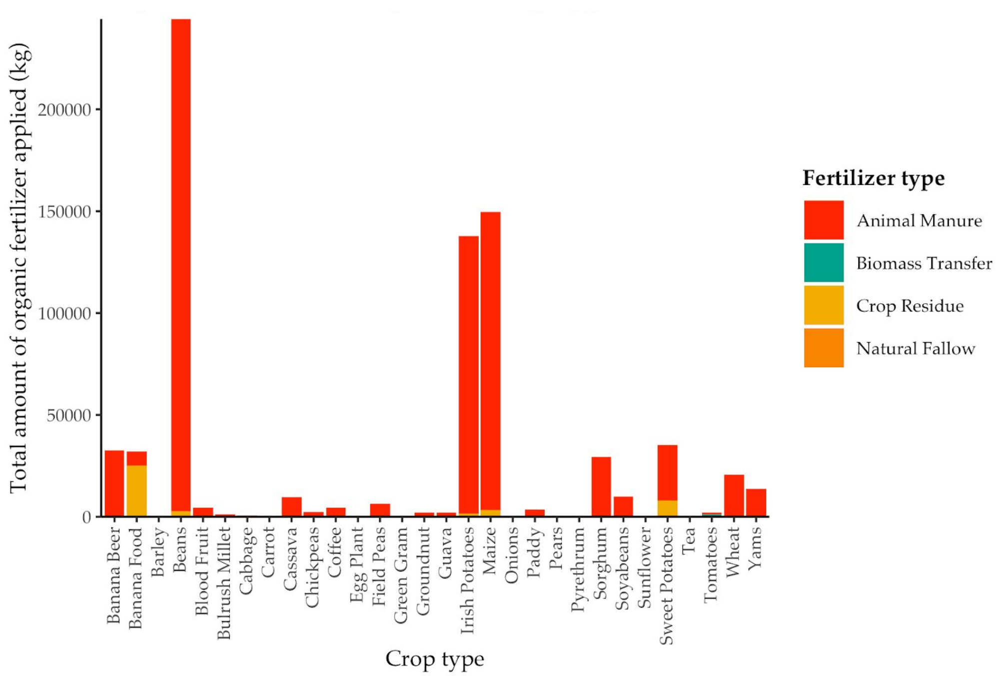

Figure A2.3 Total use of organic fertilizer (kg) by crop type over all landscapes and both rounds of data collection.

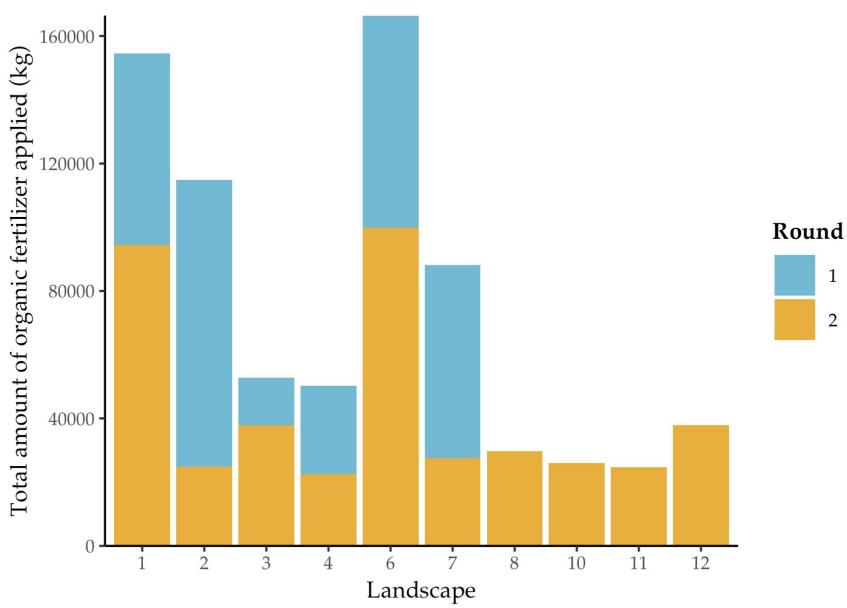

Figure A2.4 Total amount of organic fertilizer (kg) applied by landscape and round of data collection

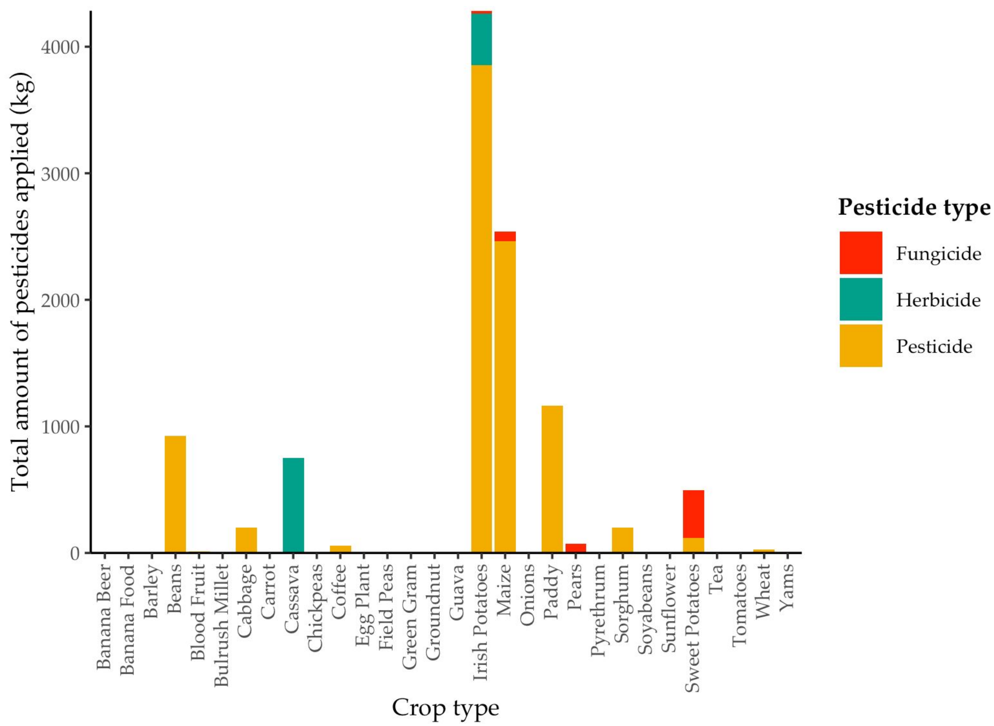

Figure A2.5 Total use of pesticides (kg) by crop type over all landscapes and both rounds of data collection.

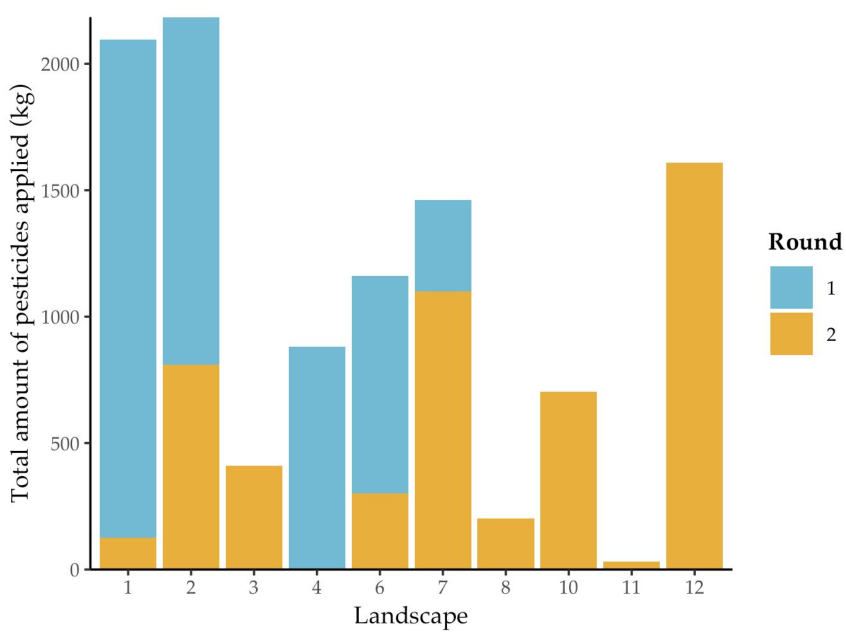

Figure A2.6 Total amount of pesticides (kg) applied by landscape number and round of data collection

Crop value by landscape

Table A1.1. Mean value (RWF/hectare) of fields for the three highest value crops in each landscape are summarized in the table below.

Landscape Number	Crop name	n	Mean value (RWF/hectare)
Landscape 1	Tea	20	2,013,800
	Irish Potatoes	53	1,178,405
	Wheat	37	610,428
Landscape 2	Blood Fruit	7	5,243,663
	Irish Potatoes	101	1,650,782
	Pyrethrum	42	739,179
Landscape 3	Paddy rice	5	1,731,515
	Banana Food	11	1,322,043
	Sweet Potatoes	5	1,141,548
Landscape 4	Sweet Potatoes	15	1,241,811
	Tea	7	729,118
	Irish Potatoes	30	462,512
Landscape 6	Yams	16	2,112,954
	Sweet Potatoes	23	1,689,984
	Banana (beer)	51	1,498,279
Landscape 7	Paddy rice	16	1,632,210
	Banana (food)	8	1,247,543
	Banana (beer)	8	527,158
Landscape 8	Groundnut	6	591,954
	Beans	50	336,905
	Sorghum	16	175,894
Landscape 10	Paddy rice	16	4,365,552
	Coffee	7	1,216,233
	Cassava	30	514,964
Landscape 11	Irish Potatoes	5	1,042,257
	Sweet Potatoes	9	727,754
	Maize	16	346,895
Landscape 12	Sweet Potatoes	5	1,073,634
	Irish Potatoes	32	564,446
	Sorghum	18	429,024